Data Mining Applications in Aeronautics and Space Exploration Workshop 2006

June 20-21, 2006

NASA Ames Conference Center NASA Ames Research Center Moffett Field, California, USA

Sponsored by the



NASA Engineering and Safety Center



Data Mining Applications in Aeronautics and Space Exploration

NASA Ames Conference Center June 20-21, 2006

Recent advances in data mining, machine learning, and statistics have enabled significant advances in numerous disciplines including aeronautics and space exploration.

The objective of this workshop was to facilitate the formation of successful collaborations between members of the aeronautics and space exploration communities. Areas of interest included:

- 1. Applications of data mining and machine learning in the aeronautics and aerospace domains;
- 2. Extraction of trends from high-dimensional heterogeneous data sets;
- 3. Clustering and classification methods for text documents;
- 4. Data-driven methods for prognosis and diagnosis of aeronautics/space systems;
- 5. Verification and validation of learning systems.

Workshop topics included new and successfully completed projects using data mining and trending techniques, unsolved problems that could be addressed by data mining but have not yet been solved, and new data mining and trending techniques.

Workshop Organizers

Ashok N. Srivastava, Ph.D. Intelligent Systems Division NASA Ames Research Center

Dawn M. McIntosh Intelligent Systems Division NASA Ames Research Center

Bob Beil
Systems Engineering Office
NASA Engineering and Safety Center

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Welcome to DMAASE 2006

Dawn Schaible and Bob Beil Systems Engineering Office NASA Engineering Safety Center

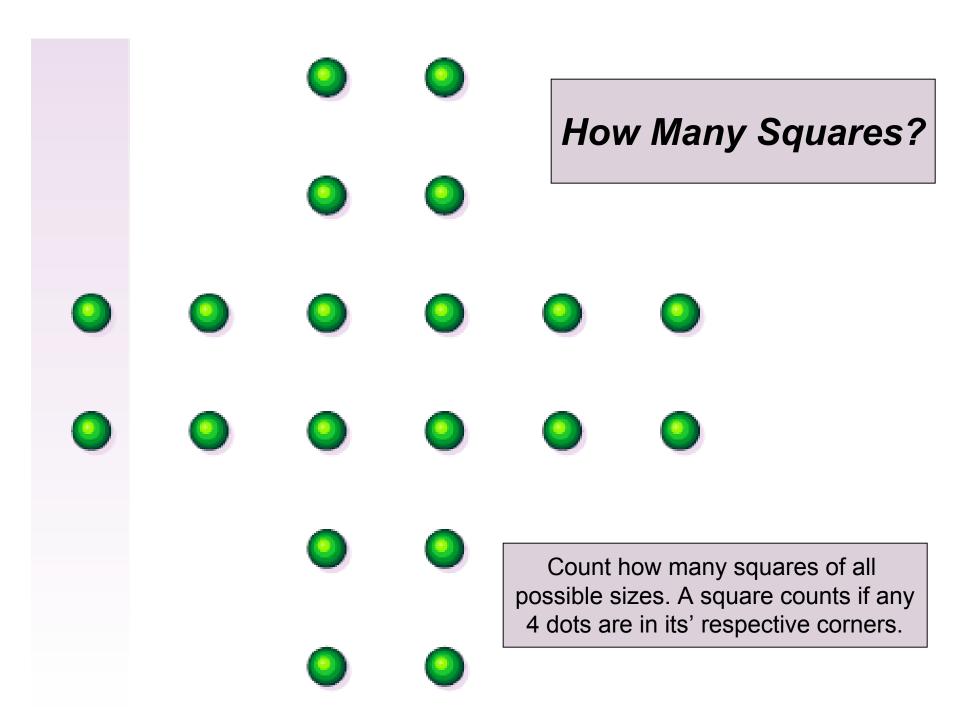
Dawn Schaible began her career with NASA at the Kennedy Space Center (KSC) in 1987, where she served as a Space Shuttle Orbiter Environmental Control and Life Support Systems (ECLSS) Engineer. In this role, she led the ECLSS ground processing activities for the Orbiter Endeavour. In 1996, Ms. Schaible joined the International Space Station (ISS) Hardware Integration Office, where she served as the Lead Test Engineer for the "Unity" Node and U.S. Laboratory "Destiny" modules. In 2000, she was selected to serve as Chief, Integration Branch for the ISS/Payload Processing Directorate. In this capacity, she was responsible for managing the launch site ground processing mission-integration activities for all Space Shuttle launched payloads and US Space Station Elements. Ms. Schaible is currently the Manager of Systems Engineering Office for the NASA Engineering and Safety Center (NESC) at the Langley Research Center, where she is responsible for providing independent trending and proactive problem identification for the NESC.

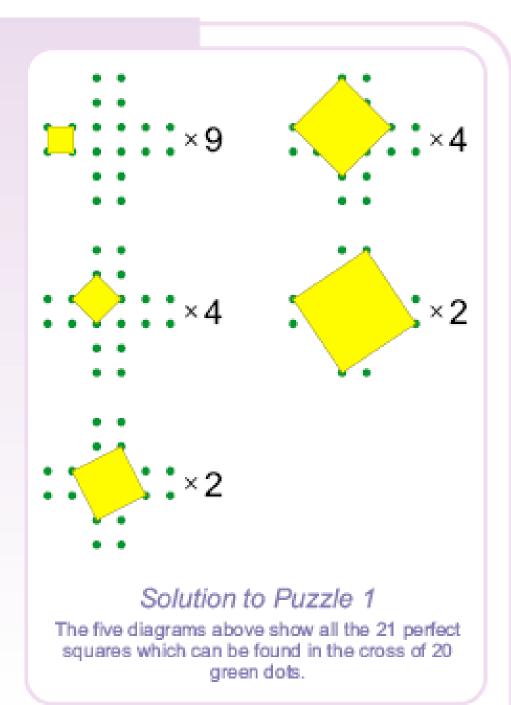
Ms. Schaible completed the Systems Design and Management Program at the Massachusetts Institute of Technology, where she received a M.S. degree in Engineering and Management. She previously received a B.S. degree in Mechanical Engineering from Bradley University and a M.S. degree in Space Systems Operations from the Florida Institute of Technology.

Bob Beil currently serves as a Systems Engineer for the NASA Engineering & Safety Center (NESC) Systems Engineering Office (SEO). His responsibilities include developing and deploying data mining and trending tools, training, and processes; participating in NESC assessments and investigations; and participating in and facilitating the Systems Analysis and Statistics super problem resolution teams.

As Orbiter Main Propulsion System (MPS) lead engineer for NASA at Kennedy Space Center, his responsibilities included implementing and coordinating Propulsion System activities in the preparation and launch of the Space Shuttle and acting as Console Chief for the cryogenic console on launch day. Additionally, he was the KSC co-chair to the Propulsion System Integration Group (PSIG), which is primarily concerned with integration and coordination of all technical areas which interface with, or have a bearing on the design, development, verification, operation, performance, and testing of the MPS. He worked on the Main Propulsion System for 16 years. In addition to MPS duties, he managed and worked on several other projects for NASA.

He earned a Bachelor of Science in Mechanical Engineering from Old Dominion University (Norfolk, VA), and a Master of Science in Industrial Engineering from the University of Central Florida.





In 1893 professor Louis
Hoffmann asked in his famous
book Puzzles Old and New to
arrange twenty counters so
that they form thirteen
different squares, and in his
original solution (he showed a
pattern exactly as our big
cross of 20 green dots) stated
that there are seventeen
perfect squares.

Several decades later, Henry E. Dudeney, England's greatest puzzle creator, improved Hoffmann's solution with 17 squares, and did this... twice - first it was a new solution with 19 squares, and then - 21. Both solutions were published in Dudeney's puzzle books.

Data Mining Workshop

Welcome & Thanks for attending

My Background

Goals for Workshop

- Build Community
- Exchange Ideas
- Learn
- Have fun
- Constellation
 - As we go through the workshop, I would ask you to think about what we need to collect to make future DMT more efficient and effective! Please jot down!!

DMTWG Information

- Breakout Session
 - Roadmap, training
 - Future workshops
- SAS training
 - Who: Data Mining & Trending Working Group
 - When: August 7-11, 2006
 - Where: Irvine, CA (SAS training facility)

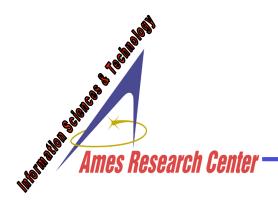
Exit Stage Left



Finding a Needle in the Haystack: Discovering and Understanding Anomalies in Complex Aeronautics and Space Systems

Ashok N. Srivastava NASA Ames Research Center

Dr. Ashok Srivastava is a Principal Scientist and Group Lead in the Intelligent Data Understanding Group at NASA Ames Research Center. He has seventeen years of research, development, and consulting experience in machine learning, data mining, and data analysis in time series analysis, signal processing, and applied physics. Specific applications in signal processing, text mining, and integrated system health management are addressed in his research.





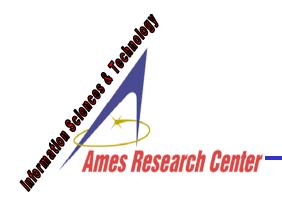
Finding a Needle in the Haystack: Discovering and Understanding Anomalies in Complex Aeronautics and Space Systems







Ashok N. Srivastava, Ph.D. Intelligent Data Understanding Group Leader NASA Ames Research Center



Group Objectives



- Delivery-oriented group that advances the state of the art in data mining, machine learning, and adaptive control
- Perform applied research in the fields such as systems health and safety, earth science, and space science
- Create tools and methods to aid in the assimilation and understanding of scientific and engineering data to best advance NASA missions
- Metrics
 - Research contributions that are recognized in the domain sciences and/or the machine learning community
 - Publications in journals and relevant conferences
 - Real-world implementations
 - 15 group members

Broad Research Goals and Application Areas

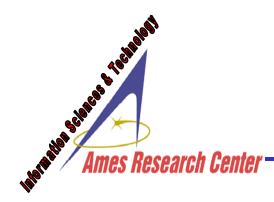




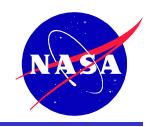
- Research Goals
 - Scientific Data Understanding
 - Forecasting and
 Understanding Time-Based
 Data
 - Machine Learning for Optimization
 - Understanding Complex Physical Systems

- Application Areas
 - Systems Health
 - Earth Sciences
 - Space Sciences





The Team



Ashok Srivastava, Ph.D.
Suratna Budalakoti
Pat Castle
Santanu Das
Robert Delgadillo
Dave Iverson
Amy Mai
Rodney Martin, Ph.D.
Bryan Matthews
Dawn McIntosh
Matthew Otey, Ph.D.
Nikunj Oza, Ph.D.
Mark Schwabacher, Ph.D.

Eugene Turkov

Richard Watson

David Wolpert, Ph.D. Tom Ferryman, Ph.D. Battelle/PNWD Team Members are NASA, Contractors, and Students.

All schematic diagrams and pictures in this presentation are publicly available on the internet.

Advance Engineering Network Team Summer Students from UCSC Aviation Safety Program NESC

6/20/06



Overview



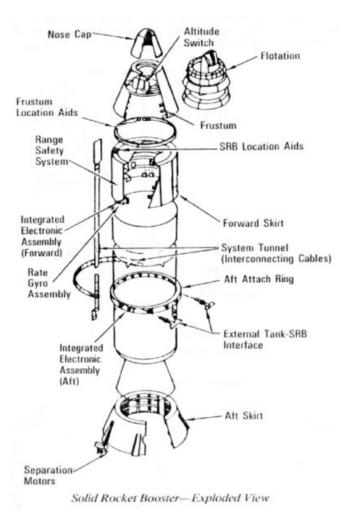
• Aeronautics and Space Systems have vast data stores associated with them, including continuous, discrete, and text data.

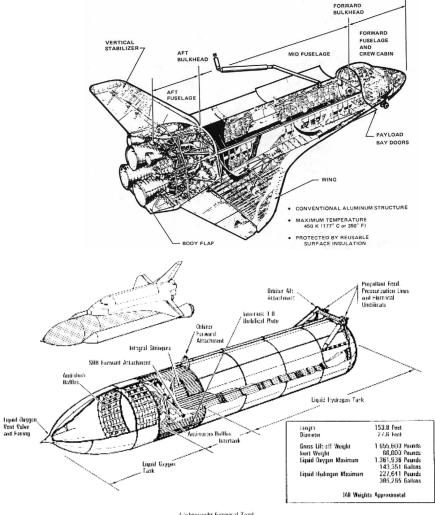
• We will overview recent results on discovering anomalies from these sources.

Some systems we are considering



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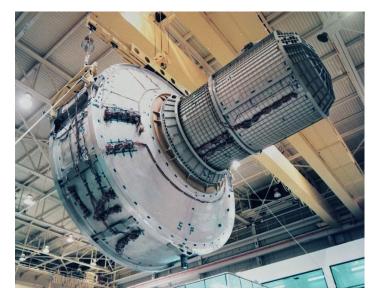
Lightweight External Tank

International Space Station

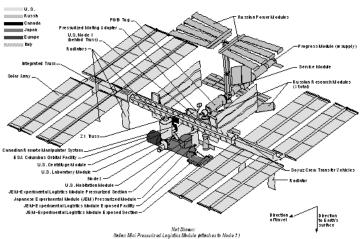


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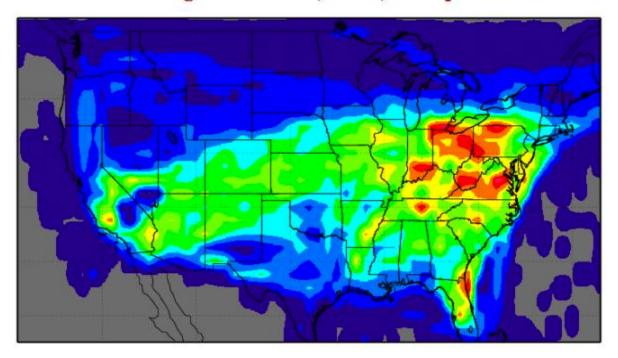
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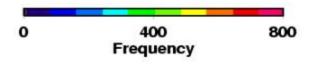


The National Air Space



Number of flights above 25,000 ft, 10 September 2001







Problem Reports



- Each system can have several hundred thousand reports written about them.
- Hundreds or thousands of different authors.
- In some cases, different languages are used.
- Reports can be 0.5-4 pages long.
- Each system has its own set of acronyms.
- These systems have been around for decades and are continuously being modified.
- Each author has his or her own perspective.

Did you ever wonder what those strange conglomerations of letters meant? Here's your chance to find out what those NASA acronyms stand for. About Space and Astronomy presents the Guide to NASA Acronyms. From Navigation and Guidance to Network Interface Data System - NASA Management Instruction to Nose to Z-Axis, you'll find them here. This page lists acronyms starting with N. For others, click on the appropriate letter above or below.

```
N: Neutrons
N: Newton
N: North
```

N&G: Navigation and Guidance (G&N preferred)

N/0: Normally Open N/A: Not Applicable

N/A: Next Assembly

N/B: Narrow Band N/C: Numerical Control N/C: Normally Closed

N/C: Nose Cone N/C: Not Critical N/D: Need Date N/P: Not Provided

N/W: Network

NO2: Nitrogen Dioxide N2: Nitrogen N2: Nitrogen

N204: Nitrogen Tetroxide N2H4: Hydrazine

N2HO4: Nitrogen Peroxide N2O4: Nitrogen tetroxide NA: Next Action

NA: Not Applicable
NAAL: North American Aerodynamic Laboratory (Wind Tunnel) NAC: Nacelle

NAEC: Naval Air Engineering Center NAM: National Association Of Manufacturers

NAP: Navigation Analysis Program

NAR: Numerical Analysis Research NARS: National Archives and Record Services

NAS: National Aircraft Standard

NAS: National Academy of Sciences

NAS: Naval Air Station

NASA: National Aeronautics and Space Administration NASA: National Aeronautics and Space Administration

NASCOM: NASA Communications (Network)

NASTRAN: NASA Structural Analysis NATF: Naval Air Test Facility

NAV: "Navigate, Navigation' NAVAID: Navigation Aid

NAVDAD: Navigationally Derived Air Data

NAVPOOL: Navigation Parameter Common Pool NAVSAT: Navigation Satellite

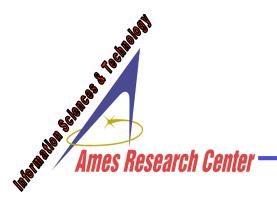
NB: Navigation Base NB: No-Bias (Relay) NB: Nitrogen Base

NB: Narrow Band

NBF: Neutral Buoyancy Facility

NBS: National Bureau of Standards

NBT: Neutral Buoyancy Trainer



Problem Definition



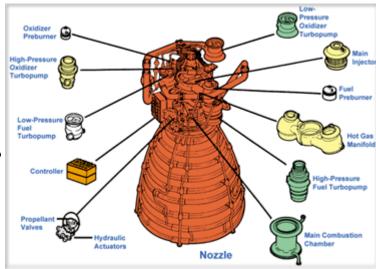
- Develop a system that will automatically discover recurring anomalies given a stack of 100,000+ reports.
- Some types of reports are pre-classified into anomaly categories. Others are not classified into categories.

A recurring anomaly is a reported problem that happens

more than once regarding:

The same system

- Similar systems
- Functionally related systems





Fingerprints of Anomalies

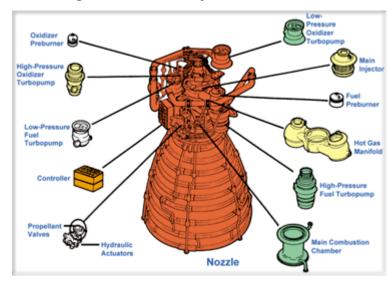


Identifiable Anomalies

- Recurrent failures
- Problems that cross traditional system boundaries so failure effects are not fully recognized
- Problems that have been accepted by repeated waivers
- Discrepant conditions repeatedly accepted by routine analysis
- Events with unknown causes

Hard to Identify

- Single failures
- Identification of the root cause of anomalies that propagate through several systems

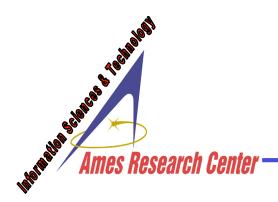




Why not just...



- Have people read the reports and come up with recurring anomalies?
- Use a search engine?
- Do keyword search?
- Generate good forms to collect data to enable discovery of anomalies?
- Focus on sensor data?



Types of Reports



Problem Reporting And Corrective Action (PRACA)

- Usually for engineering systems such as Shuttle, ISS
- Usually have sections describing each element
- *Usually* are not pre-assigned into anomaly categories
- Written by engineers and scientists

Aviation Safety Reporting System (ASRS)

- Publicly available safety reports regarding commercial airliners
- Are categorized into one of 62 anomaly categories
- Written by pilots, crew, maintenance workers

Aviation Safety Action Program (ASAP)

- Safety reports for major airlines (AA, UAL, etc.)
- Are not pre-categorized
- Written by pilots, crew, maintenance



Summary of Approach



Approach for PRACA data

- These reports *do not* have an anomaly category
- We first perform von-Mises Fisher clustering to break the corpus into groups.
- Develop similarity measures.
- Use an agglomerative clustering technique to link documents.
- Documents linked early may be recurring anomalies.
- Link documents that reference each other.

Approach for ASRS data

- These reports *are* preclassified into anomaly categories.
- Develop Natural Language Processing (NLP) techniques to identify terms and phrases related to anomalies.
- Build classifier(s) to learn mappings from documents to categories.
- Test quality of classifiers.
- Apply to new corpora from airlines that have no categorization.

von-Mises Fisher Clustering



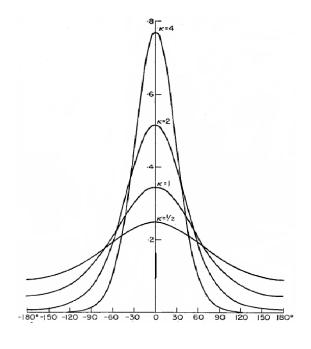
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- Innovation by Banerjee,
 Dhillon, Ghosh, and Sra 2005.
- Idea: convert document vectors into directional data by normalizing to unit length.
- Create a generative model for a d-dimensional document vector x of unit length:

$$f(\mathbf{x}|\boldsymbol{\mu}, \kappa) = c_d(\kappa)e^{\kappa \boldsymbol{\mu}^T \mathbf{x}},$$

$$c_d(\kappa) = \frac{\kappa^{d/2-1}}{(2\pi)^{d/2} I_{d/2-1}(\kappa)}$$

Density of the von Mises distribution for $\mu_0 = 0^{\circ}$ and $\kappa = \frac{1}{2}$, 1, 2, 4.



Bessel function of the first kind, order d/2-1

Why Ames Research Center

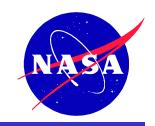
Why is VMF a good model for text?



- Document vectors are L₂ normalized to make them unit norm.
- Assumption: Direction of documents is sufficient to get good clusters.
- Two documents one small, one lengthy on the same topic will have the same direction and hence put in the same cluster.
- This unit normalized data lives on a sphere in a R^(d-1) dimensional space.



Connections with the Normal Distribution



• A circular random variable ' θ ' follows a von Mises Distribution if its pdf is given by:

$$g(\theta; \mu_o, \kappa) = \frac{I}{2\pi I_o(\kappa)} \exp \kappa \cos(\theta - \mu_o),$$

$$0 \le \theta \le 2\pi, \kappa > 0, 0 \le \mu_o \le 2\pi$$

For large K the random variable ' θ ' is distributed as $N(\mu o, 1/K^{1/2})$

Relation to Bivariate Normal Distribution:

Let x and y be independent normal variables with means $(\cos \mu o, \sin \mu o)$ and equal variances 1/ K. The p.d.f. of the polar variables (r, θ) is VMF The conditional distribution of θ for r = 1, is the VMF(μo , K).

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Connections with Normal II



- Maximum Entropy Characterization:
 - Given a fixed mean and variance the Gaussian is the distribution that maximizes the entropy.
 - Likewise given a fixed circular variance ρ and mean direction μ_o , the VMF distribution maximizes the entropy.
- Central Limit Theorems
 - For data on a line, the CLT says that the Normal is the limiting distribution.
 - Whereas for directional data, the limiting distribution of the sum of 'n' independent random variables is given by the Uniform Distribution.

Conter-

Connections with the Normal Distribution



Unfortunately there is no distribution for directional data which has all properties analogous to the linear normal distribution. The VMF has some but not all of these desirable properties.

The VMF provides:

- simpler ML estimates
- tractable distribution in hypothesis testing

See Banarjee et. al. for details of the maximum likelihood estimates and the EM derivation.



Similarity Measures

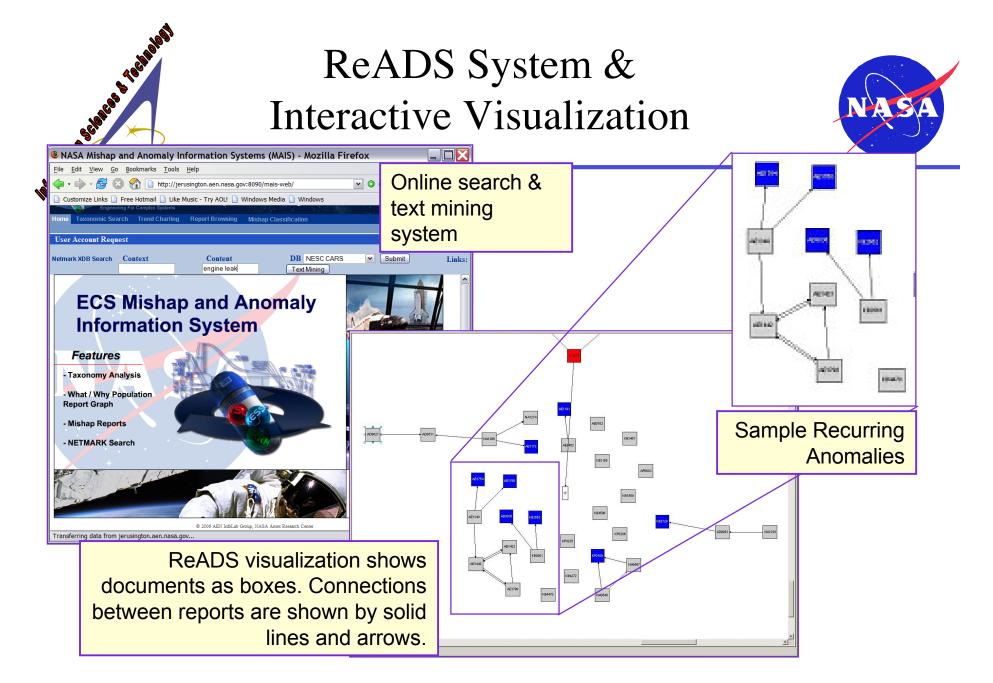


- The vMF distribution implies that the cosine measure between documents is a natural similarity measure.
- We tested numerous other measures by assuming a language model (see Srivastava et. al., 2005) and measuring the distance between the distributions of words using Kullback-Leibler.
- All methods performed identically within the error bars.

Discovering Recurring Anomalies

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- After calculating the distance between each document, the algorithm applies single linkage, i.e., nearest neighbor, to create a hierarchical tree representing connections between documents.
 - Also generates an 'inconsistency coefficient' which is a measure of the relative consistency of each link in the tree.
- The hierarchical tree is partitioned into clusters by setting a threshold on the inconsistency coefficient.
 - A high inconsistency coefficient implies that the reports could be very different and still be sorted into the same cluster.
- Currently the inconsistency coefficient threshold is set very low, which returns many smaller clusters of very similar reports.
 - Clusters of single documents are excluded from the recurring anomaly results.



Recurring Anomaly Detection System- ReADS

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How well does the system work?

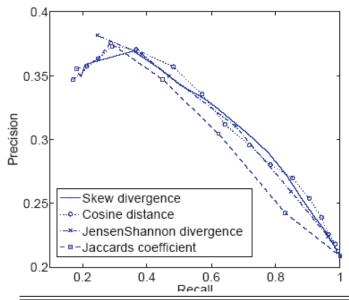


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- We compared the results of our system against a set of recurring anomalies identified by humans on a sample data set of nearly 7400 reports.
- We discovered many recurring anomalies that were missed by the experts.
- We missed anomalies and also had a relatively large false positive rate.

$$Precision = \frac{R^+}{R^+ + N^+}$$

$$Recall = \frac{R^+}{R^+ + R^-}$$



	Labeled by Expert as recurring anomaly	Not labeled by Expert as recurring anomaly
Detected as recurring anomaly	R ⁺	N ⁺
Not detected as recurring anomaly	R ⁻	N^-

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ASRS Anomaly Classification



- These reports are already coded into 60 overlapping categories.
- We developed Natural Language Processing techniques to preprocess this data before submission to SVM for classification.



Sample Language Normalization & Term Reduction

JUST PRIOR TO TOUCHDOWN, LAX TWR TOLD US TO GO AROUND BECAUSE OF THE ACFT IN FRONT OF US. BOTH THE COPLT AND I, HOWEVER, UNDERSTOOD TWR TO SAY, 'CLRED TO LAND, ACFT ON THE RWY.' SINCE THE ACFT IN FRONT OF US WAS CLR OF THE RWY AND WE BOTH MISUNDERSTOOD TWR'S RADIO CALL AND CONSIDERED IT AN ADVISORY, WE LANDED. AS WE TAXIED TO THE GATE, TWR REQUESTED THAT I CALL THEM FROM A PHONE WHEN I HAD THE OPPORTUNITY (I CALLED FROM THE GATE). IT WAS ON THE PHONE THAT I DISCOVERED TWR HAD SENT US AROUND. IN HINDSIGHT, FROM THEIR PERSPECTIVE, GOING AROUND WAS THE PRUDENT THING TO DO. I HAVE BECOME TOO CONDITIONED IN THE PAST FEW YRS IN BEING VECTORED INTO A VISUAL APCH BEHIND AN ACFT THAT IS TOO CLOSE. REGRETTABLY, IN THIS SIT, CONFUSION AND MISUNDERSTANDING PUT US IN A DIFFICULT SIT.



Expand Acronyms, Simplify Punctuation



JUST PRIOR TO TOUCHDOWN, LAX tower TOLD US TO GO AROUND BECAUSE OF THE aircraft in front of us. Both the copilot and i, however, understood tower to say, clear to land, aircraft on the runway. Since the aircraft in front of us was clear of the runway and we both misunderstand tower radio call and considered it an advisory, we LANDED. As we taxied to the gate, tower requested that I call them from a phone when I had the opportunity I called from the gate. It was on the phone that I DISCOVERED tower had sent us around. In hindsight, from their perspective, going around was the PRUDENT THING to do. I have become too conditioned in the past few year in being vectored into a visual approach behind an aircraft that is too close. Regrettably, in this situation, confusion and MISUNDERSTANDING put us in a DIFFICULT situation.



Stemming, Remove Non-Informative Terms, Phrasing



```
PRIOR _ TOUCHDOWN _ tower TOLD _ _ goaround _ _ _ aircraft _ FRONT _ _ _ _ copilot _ _ _ understand tower _ SAY clear _ LAND aircraft _ runway _ _ aircraft _ FRONT _ _ _ clear _ _ runway _ _ _ misunderstand tower RADIO CALL _ consider _ _ advise _ lan _ _ taxiedto _ GATE tower request _ _ CALL _ _ PHONE _ _ _ OPPORTUNITY _ call _ _ GATE _ _ _ PHONE _ _ discover tower _ SENT _ _ HINDSIGHT _ PERSPECTIVE go _ _ _ prudentthing _ _ _ _ condition _ PAST _ year _ _ vector _ VISUAL approach _ _ aircraft _ _ CLOSE REGRETTABLY _ _ situate confuse _ misunderstand PUT _ _ difficultsituation
```



Report before language normalization



 ON DEP FROM NARITA, JAPAN, DURING LEVELOFF AT 8000 FT, ACFT ENCOUNTERED MODERATE RAIN, HAIL, AND TURB (GPWS SOUNDED 'PULL UP) AND ACFT ALT REACHED 8400 FT. ACFT WAS PROMPTLY RETURNED TO 8000 FT. SUPPLEMENTAL INFO FROM ACN 510981: ACFT IN HVY WX/MODERATE TURB. LARGE UP-AND DOWN-DRAFTS. WENT TO 8400 FT. INADVERTENT GPWS 'WHOOP, WHOOP' DUE TO HAIL.



After language normalization



Weather

Severe Weather

Turbulence

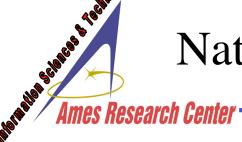
Ground Proximity Warning System activation

Resolution Advisory

Altitude Deviation

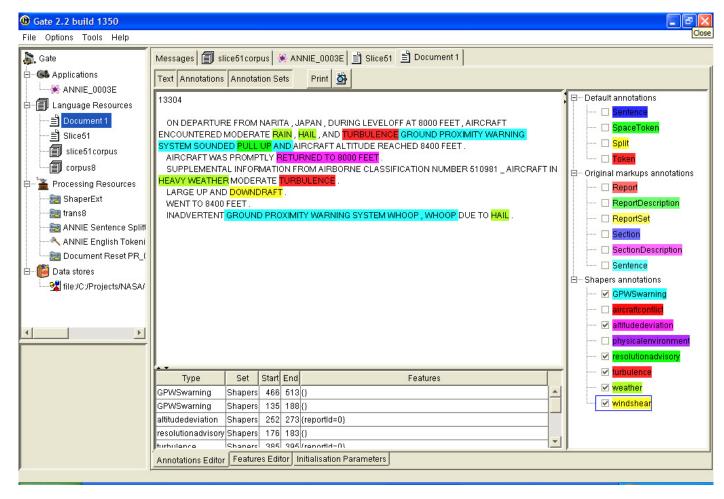
Windshear

ON DEPARTURE FROM NARITA, JAPAN, DURING LEVELOFF AT 8000 FEET, AIRCRAFT ENCOUNTERED MODERATE RAIN, HAIL, AND TURBULENCE GROUND PROXIMITY WARNING SYSTEM SOUNDED PULL UP AND AIRCRAFT ALTITUDE REACHED 8400 FEET. AIRCRAFT WAS PROMPTLY RETURNED TO 8000 FEET. SUPPLEMENTAL INFORMATION FROM AIRBORNE CLASSIFICATION NUMBER 510981 _ AIRCRAFT IN HEAVY WEATHER MODERATE TURBULENCE. LARGE UP AND DOWNDRAFT. WENT TO 8400 FEET. INADVERTENT GROUND PROXIMITY WARNING SYSTEM WHOOP, WHOOP DUE TO HAIL |



Natural Language Processing





Natural Language Processing (II)



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- ATC Communication Anomaly
- Altitude Deviations
- Airspace Violations
- Approach Anomalies
- Controlled Flight Towards Terrain
- Equipment Problem
- Fire
- Fuel
- GPWS
- Ground Encounter
- Ground Excursion
- Ground Incursion
- Hazardous Materials Violation

- In-flight Encounters
- Landing Anomalies
- Loss of Control
- Maintenance Problem
- Near Miss
- Passenger/Cabin Event
- Speed Deviation
- Takeoff Anomalies
- TCAS
- Turbulence
- Unstabilized Approach
- Weather
- Windshear

Over 200 building block concepts mapped to 39 Major Categories

Examples of NLP predictions for "Turbulence" Anomaly



- THE AIR WAS VERY TURBULENT, THE FREEZING LEVEL WAS AT 10000 FEET MEAN SEA LEVEL, WIDESPREAD SHOWERS OBSCURED THE MOUNTAINS NORTH OF THE TEMPORARY FLIGHT RESTRICT, AND WE HAD INSUFFICIENT FUEL TO RETURN TO MCCALL, IDENTIFY MLY, TO LAND.
- WE HAD JUST FINISHED WITH OUR FIRST BEVERAGE SERVICE, WHEN HEAVY TURBULENCE HIT.
- BECAUSE OF THE TURBULENCE, MY HAND INADVERTENTLY HIT THE VOLUME CONTROL AND LOWERED THE VOLUME TO AN INAUDIBLE LEVEL WITHOUT DETECTION BY THE CREW.
- COULD NOT MAINTAIN VISUAL METEOROLOGICAL CONDITIONS IN THE TOPS AND STARTED TO GET LIGHT PRECIPITATION AND LIGHT TO MODERATE CHOP.
- A PASSENGER VIEWING THE MANDATORY VIDEO BEFORE FLIGHT FULLY UNDERSTANDS THE RESULTS OF NOT WEARING A SEATBELT IF SHOWN POSSIBLE SCENARIOS INCLUDING UNEXPECTED TURBULENCE AND STOPPING SHORT ON THE RUNWAY DURING TAXI.

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Example of False Negative



I PARKED BEHIND THE HOLD SHORT LINE AT THE RUNUP AREA OF RUNWAY 18 AND PROCEEDED TO COMPLETE THE BEFORE TAKEOFF CHECKLIST. AFTER COMPLETING THE BEFORE TAKEOFF CHECKLIST, I TAXIED THE AIRPLANE INTO A POSITION TO CLEAR THE BASE AND THE FINAL APPROACH PATH FOR INCOMING TRAFFIC. NO TRAFFIC WAS OBSERVED ON THE FINAL OR BASE. ADDITIONALLY, NO RADIO CALL WAS MADE BY THE INCOMING AIRCRAFT. NOT SEEING OR HEARING ANY AIRCRAFT ON A FINAL APPROACH, I PROCEEDED TO CROSS THE HOLD SHORT LINE AND TAXIED ONTO THE RUNWAY. AS I ALIGNED THE AIRCRAFT WITH THE RUNWAY CENTERLINE, AN AIRCRAFT FLEW OVER MINE AND EXECUTED A MISSED APPROACH.

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Raw Text & Language Normalization



In order to classify the documents, they are first formatted into a document-term frequency matrix. The cells of the matrix are the frequency count of the terms that appear in the document.

	Term I	Term 2	Term 3	Term 4
Document I	0	_	0	4
Document 2	0	3	0	0
Document 3	2	8	I	0

- PLADS reduced the total number of terms in 27000 documents from 44940 to 31701
- PLADS reduced classification computation time by 0%-10%

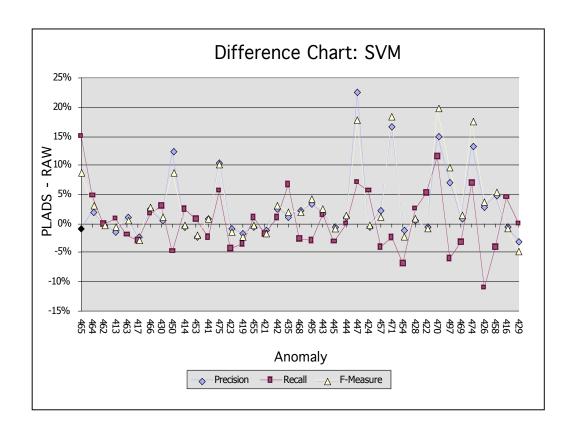
Comparison of Raw Text vs. Language Normalization using SVM



• All terms used, no additional term reduction applied

Ames Research Center

- Language Normalization improves precision 2% on average
- Language Normalization improves recall 2% on average



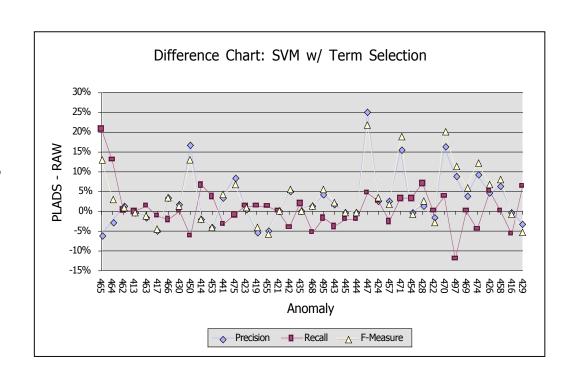
Comparison of Raw Text vs. LN with Terms Selection



• 1000 terms selected using Information Gain

Ames Research Center

- LN improves precision 2% on average
- LN improves recall 3% on average

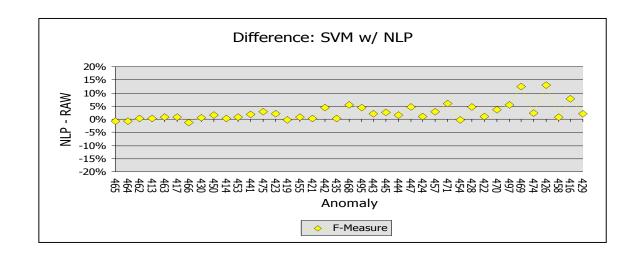




Comparison of Raw Text vs. NLP with Terms Selection



- 500 terms selected using Information Gain
- NLP improves Fmeasure 3% on average

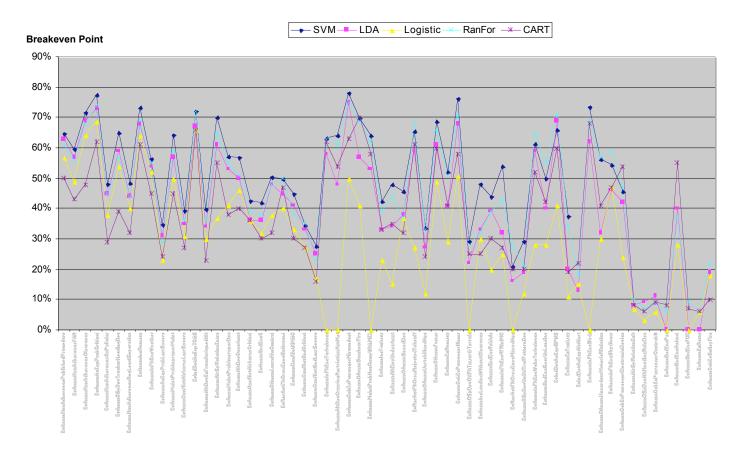




Overall Results without NLP



No NLP Terms



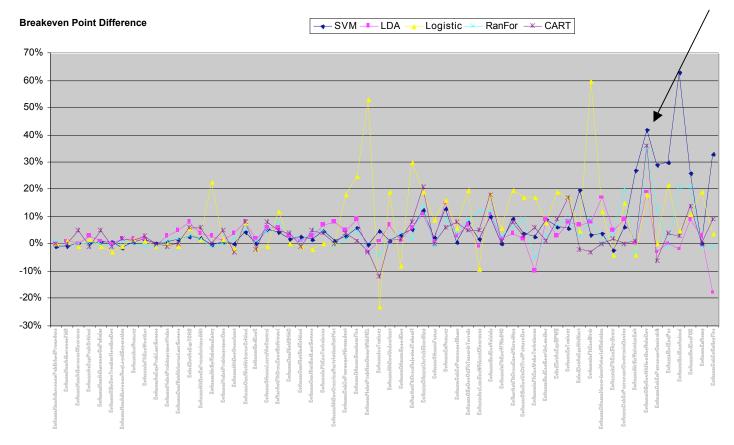


Difference



Spike is due to the fact That SVM was not run On these categories.

Difference (NLP - No NLP)

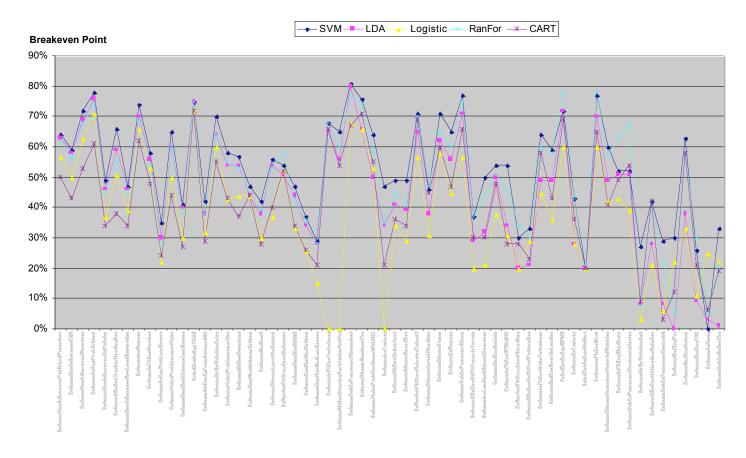




Results with NLP



With NLP Terms

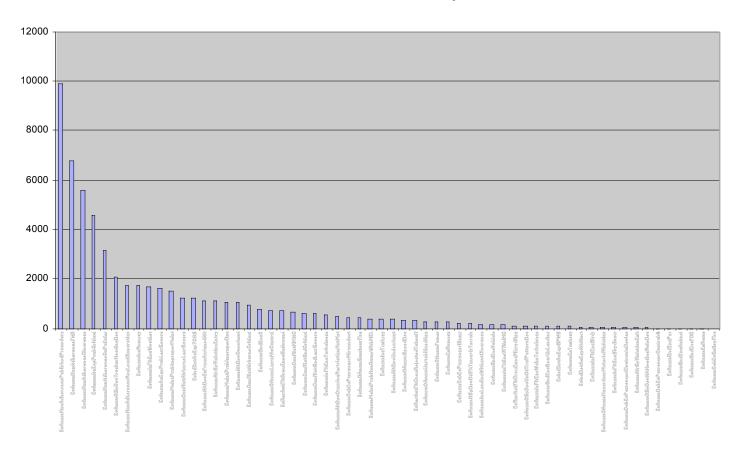




Anomaly Frequencies



Number of Hits for each Anomaly



Summary and Conclusions



- For clustering documents we find that the distributional approach suggested by Banerjee et. al. works well.
- We have discussed some reasons why vMF clustering may be useful in this application.
- We have explored the use of NLP and language normalization in detail for classification purposes.
- Results indicate no significant benefit in this classification task although the NLP methods used were extremely expensive.
- Data is available at http://ti.arc.nasa.gov/people/ashok

Ames Research Center



Discovering Atypical Flights in Sequences of Discrete Flight Parameters

Suratna Budalakoti (UCSC) Ashok N. Srivastava, Ph.D. (NASA) Ram Akella, Ph.D. (UCSC)



Motivation/Project Aims

- Discrete parameters recorded by flight sensors in commercial airliners contain valuable information.
- This information is usually not exploited. Little or no analysis currently takes place currently on the discrete sensor data.



Motivation/Project Aims

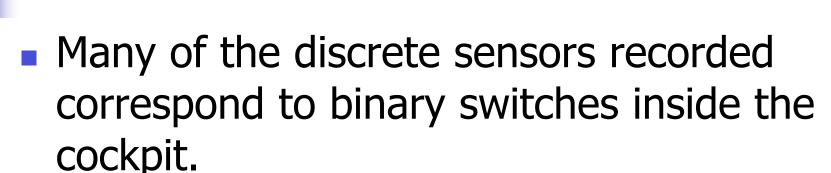
- The discrete parameter information can be used to recognize existing/potential anomalies, that may be indicative of a problem.
- The ultimate goal of the system is to help safety experts discover significant human factor issues such as pilot mode confusion.



Related Work

- The Morning Report
 - Mathematical techniques (PCA and clustering) used tailored to continuous sensor data. May not be suited to discrete data.
 - Disregards the sequential nature of the sensor information.





 Unlike continuous sensors, the sequence in which these switches change values during the course of a flight is significant.



Contributions

- We describe algorithms that are able to take into account the sequential nature of discrete parameters, and which:
 - Detect flights with anomalous behavior and provide an estimate (or ranking) of how anomalous these flights are.
 - Detect regions inside an anomalous flight that deviated from expected behavior.



Data Description

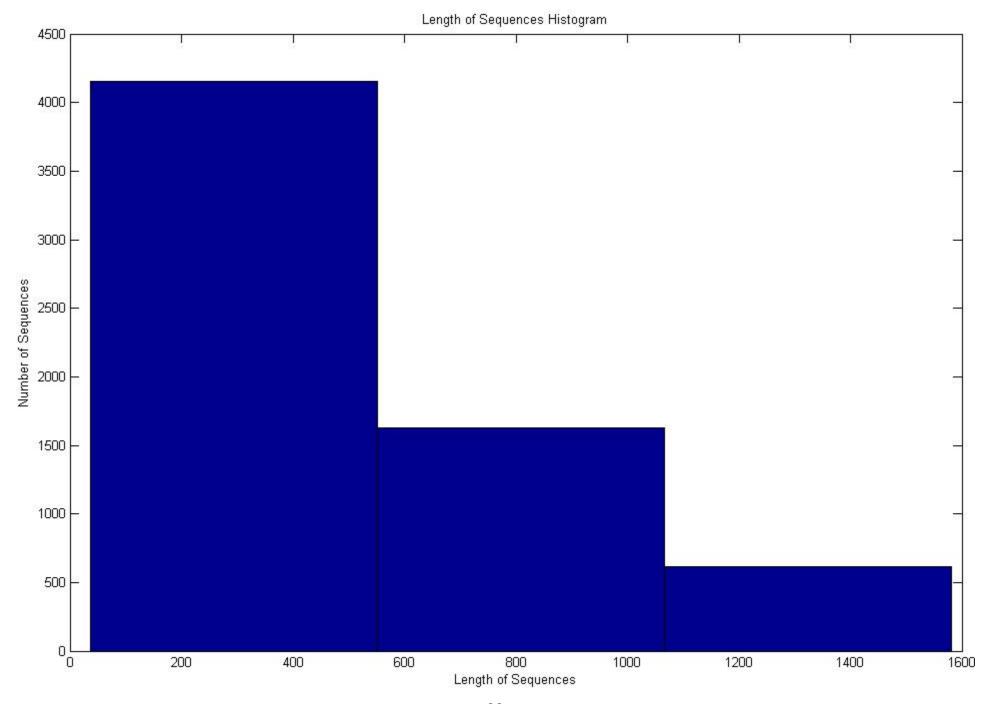
 Discrete binary sensor (switch) data collected during aircraft flight.

 Recordings made by sensors at certain intervals during the course of flight.



Data Transformation

- Store the initial value of each switch(0/1).
- At each time point, record only those switches that make a transition.
- This gives us a sequence describing the order in which switches were flipped during the course of the flight.

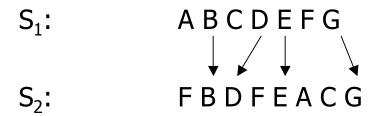




- Cluster flight sequences into groups of high similarity.
- Outlier flights, i.e., flights which have low similarity with the cluster they belong to, are considered anomalous.
- Measuring Similarity between sequences:
 - Normalized Longest Common Subsequence
- Clustering algorithm used: CLARA (Clustering LARge Applications)



 Measures how many switches followed the same order between two flights, compared to the total number of all switches flipped during the flights.

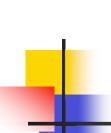


- Subsequences may be non-contiguous.
- Divided by the average length of the two sequences.



Clustering Results:

- Clustering done over 6400 flights.
- Number of switches flipped during a flight vary over a wide range, between 600 and 9000.
- Clustering produces one large group of around 4700 flights. A high average similarity of 0.75 for the largest cluster.
- Around 75% of the switches are generally flipped in the same order for most flights.



Task 2: Finding anomalous events inside a flight.

Approach:

- Use the longest common subsequence measure to establish the areas that are in the right order in comparison to a 'majority' of the flights.
- The switch sequences the anomalous flight does not share with other flights (below a mathematically calculated threshold) are the anomalous sequences inside the flight.

Cases the algorithm can detect: Expected Insertions

One or more switches were expected at a given stage but were not flipped.

Example:

Usual: 101 105 102 105 * 103 * 107 * 106

Anomalous: 101 105 102 105

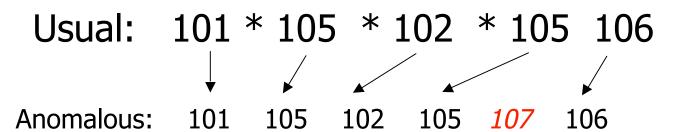
106

The algorithm will suggest 103, 107 be inserted after 105.



Expected Deletions

- One or more switches were not expected at a given stage but were flipped.
 - Example:



The algorithm will suggest 107 be deleted from after 105.



Switches in the wrong order

 One switch is always flipped after another at a given stage, but was flipped before in this case.

Example:

Usual: 101 103 105 * * 107

Anomalous: 101 103 107 * * 105

- The algorithm will suggest 105 be deleted from its location and inserted between 103 and 107.
- The number of switches between 107 and 105 is irrelevant to the sensitivity of the algorithm.



Anomaly Score

- A score is assigned to each anomaly, which measures how much it deviates from the norm.
- In the previous version, the score did not take into account the type of switches involved in the anomaly.
- However, all switches are not created equal:
 - A pilot talking to the control tower at an unexpected point in a flight is not the same as missing a significant step of the landing phase.



Nature of a Switch

- Statistical analysis shows:
 - Each switch has its own probability of alignment in a sequence.
 - The probability varies from 5%-90%.
 - Certain switches are almost perfectly aligned across flights, i.e., they are always pressed at the same point in the flight.
 - Some switches are almost never aligned.



Nature of a Switch

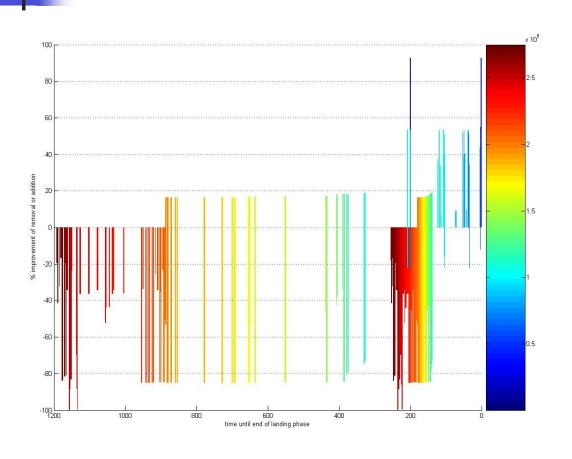
- Switches that are usually aligned, or occur in the same location in all flight sequences, should be more important to the flight.
- A utility value is assigned to the misalignment for each switch. The value is inversely proportional to the log-likelihood of alignment of the switch.
- The new score is now a function of:
 - The location of the anomaly.
 - And also, the nature of the switches involved in the anomaly.



Reducing false alarms: Ignore deviations with a small time gap

- Suppose the algorithm calculates a switch should have been pressed at a certain time, but was not pressed.
 - It searches to see if the switch was pressed within one minute of the expected time.
 - If the switch was pressed within a minute of the time point, it ignores the alarm.
- This step reduces alarms by around 30%.

Sample Output over a selected flight



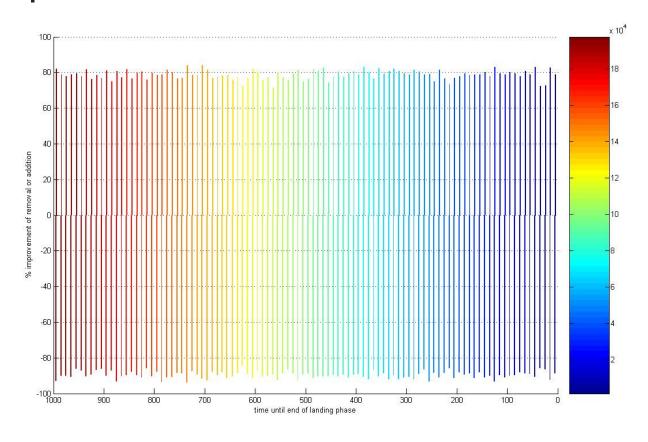
- X-axis: Time to landing
- Y-axis: Degree of Anomalousness
- Color of bars represents altitude
- +ve Y-axis: Switches expected to be pressed but not pressed.
- -ve Y-axis: Switches pressed at an unexpected location.



Test Example:

- A set of sequences was synthetically generated with an average similarity of 0.8, to mimic the clusters found in data.
- A new 'clean' sequence was chosen, and switches at every 50th and 51st location in this sequence were swapped.

System Result over Test Example



 An addition and a deletion anomaly at every 50th and 51st location



Operational Significance:

 Should be able to successfully detect any significant departure from Standard Operation Procedure(SOP) in a flight.

 Is flexible. Does not have a single specific SOP stored as part of system. 'Learns' the SOP from the data presented to it.



Conclusions

- We have overviewed methods to discover anomalies in text and discrete data sets.
- Similar methodology with very different implementations.
- New algorithms need to be created and evaluated: standard methods do not exist for many problems.

The Morning Report: Advanced Pro-active Safety and System Monitoring Tool

Tom Ferryman Battelle/Pacific Northwest National Laboratory

Dr. Tom Ferryman, Chief Scientist for Math/Stat at Pacific Northwest National Laboratory, has 35 years of experience in a variety of R&D projects including development of data analysis tools to detect typical patterns and atypical events. He led the algorithm development of The Morning Report for NASA, which won an R&D 100 Award in 2005.



The Morning Report: Advanced Pro-active Safety and System Monitoring Tool

Product with the An Invention by: NASA Ames Research Center **Battelle & the Pacific Northwest National Laboratory ProWorks**

June 2006

Why do we need: The Morning Report: Advanced Pro-active Safety and

System Monitoring Tool

- ► Aviation Safety
 - Aviation is one of the safest ways to travel in the world.
 - Why does it warrant efforts to monitor and improve?
 - Number of flights is expected to double in the next few years, which means the number of accidents is likely to double (or worse).
 - Changes in the airspace can have subtle and unenvisioned but significant impact on safety.
- ► Monitoring 1000s of flights every day is almost impossible, but we can monitor:
 - 10-20 typical patterns (with ~99% of the flights)
 - 10-20 atypical flights



How to do it, without major effort? The key elements of the approach

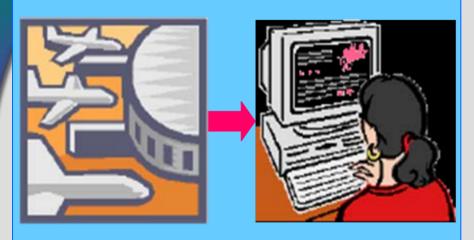
- 1. On-board instrumentation records hundreds of variables for every flight.
 - Roll, pitch, airspeed, engine temperature, vibrations, etc. are recorded every second from engine start to engine shut down
- 2. Sophisticated statistical analysis that analyzes the data to find:
 - Typical patterns, that characterize 99% of the flights
 - Atypical events, that are worthy of individual inspection
- 3. <u>User-friendly software</u> enables the user to rapidly and effectively drill into the gigabytes of data to find the insight needed to:
 - Understand safety issues and formulate corrective plans if appropriate
 - Monitor typical patterns for trends
- 4. <u>Aviation Experts</u>, inspired by new insight, proactively identify and correct safety issues affecting aviation safety

The Morning Report invention enables this by providing:

- 1. Sophisticated statistical analysis
- 2. User-friendly software

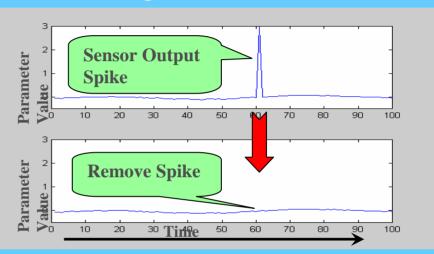


Step 1: Download Data



- Download daily or weekly
- From tapes, disks, or solid state devices
- Use commercially available playback software
- Insert data into commercially vended database

Step 2: Check the Data Quality



- Apply knowledge-based filters
- Identify "bad" data
- Remove the "bad" data
- Inform user of QA problems

PRE-PROCESSING

Step 3: Conduct Pre-defined Exceedance Checks

- Airline experts define specific data comparisons to be made at specific routine events
 - Are the gear down while altitude is above 18,000 ft?
 - Are the flaps extended while airspeed is greater than 300 knots?
 - Etc.

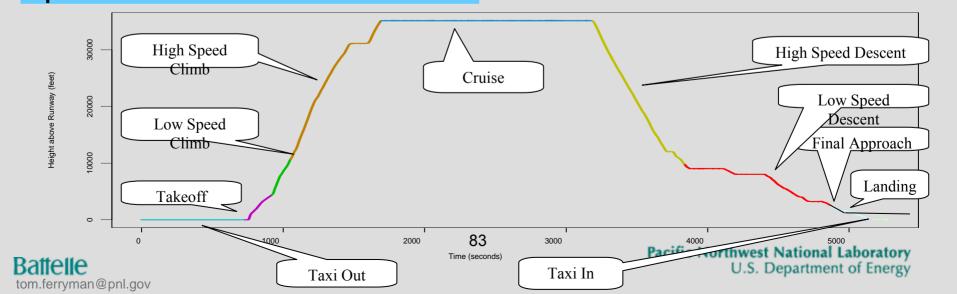
	Time (secs)	Param 1	Param 2	 Param P	Routine Events
	1	103.40	1	277.40	Start Takeoff
	2	103.70	1	266.30	
	126	104.49	1	267.31	
	127	104.98	1	268.19	
	. _				
	129	105.45	0	269.12	Gear Up
	100	105 70	^	202 72	
	131	106.39	0	269.78	
	4021	106.82	0	270.71	
	4022	107.33	0	270.78	
	4023	107.89	0	270.85	10000 ft AFE
	4024	108.40	0	271.14	
	4025	108.53	0	271.53	
	4026	109.38	0	272.03	
	N	110.68	0	273.70	Touchdown

This requires that we <u>envision</u> the potential problems before they occur.

Step 4: Structure the Data

- Data are parsed into flight segments
- Flight Segments based on Event Markers, e.g.
 - Gear-up
 - Cross outer-marker
 - Descent through 1000 ft AFE
- Customizable to each air carrier phase definitions

Time (secs)	Param 1	Param 2	 Param P	Event Marker	ACR Phase
151					
152	103.40	1	277.40	Rotate	Takeoff
153	103.70	1	103.70		
335	105.13	1	105.13		
336	105.45	0	105.45	Gear Up	
337	105.73	0	105.73		
			 		climb
1225	106.82	0	106.82		
1226	107.89	0	107.89	10000 ft AFE	
1227	108.10	0	108.07		
3236	108.51	0	109.04		
3237	109.33	0	109.12	Max Altitude	Cruise
3238	110.25	0	109.74		
6259	109.04	0	108.60		
6260	109.85	0	109.57	10000 ft AFE	
6261	109.87	0	110.39		
			 		Approach
6673	110.70	0	110.53		
6674	111.19	0	110.68	Gear Down	
6675	111.90	1	111.29		
7786	112.13	1	112.10		Landing
7787	112.91	1	112.43	Touchdown	
7788	113.63	1	112.90		



Step 5: Create Derived Parameters to Capture Physics Based Insights

- Aircraft heading with respect to runway
- Aircraft location with respect to runway
- Derived Energy Parameters
 - Total energy
 - Kinetic energy
- Others

Step 6: Calculate Preliminary Flight Parameter Signatures

- Continuous Variable
 - Air speed, roll, altitude, vibration, etc.
- Discrete Variables
 - Gear position, autopilot mode, reversers status, etc.
- Data Compression Signature
 - Lossy compression for continuous variables
 - Lossless compression for discrete variables

Step 7: Store the Signatures into the Database

Analysis

- ► The previous steps (Steps 1-7) are performed once for each flight.
- ➤ After many flights are collected, then in Steps 8-11, we compare the flights to each other and identify
 - Typical patterns
 - Atypical events
- ▶ Then we share the information with the user.



Step 8: Select the Data

- Select a subset of data:
 - Aircraft type
 - Airports
 - Flight Phase
 - Time Frames
 - Other Parameters

Time (secs)	Param 1	Param 2	Param P	Event Marker
Time (Secs)		raiaiii Z		
1	103.40	1	277.40	Start Takeoff
2	103.70	1	266.30	
126	104.49	1	267.31	
127	104.98	1	268.19	
129	105.45	0	269.12	Gear Up
130	105.73	0	269.73	
131	106.39	0	269.78	
4021	106.82	0	270.71	
4022	107.33	0	270.78	
4023	107.89	0	270.85	10000 ft AFE
4025	108.53	0	271.53	
4026	109.38	0	272.03	
N	110.68	0	273.70	Touchdown

Time (secs)	Param 1	Param 2	 Param P	Event Marker
129	105.45	0	269.12	Gear Up
130	105.73	0	269.73	
131	106.39	0	269.78	
4021	106.82	0	270.71	
4022	107.33	0	270.78	
4023	107.89	0	270.85	10000 ft AFE

Step 9: Transform the Signatures

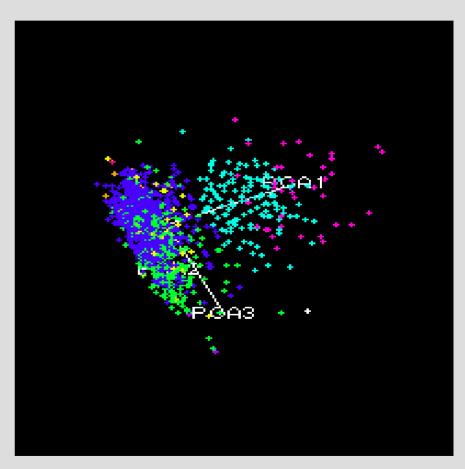
- Multivariate mathematical statistical techniques used enable:
 - Time series analysis
 - Independent of phase duration
 - Flight mode transitions
 - Captures values, trends, & noise
- The users are mercifully shielded from having to understand these details.

	Time (secs)	Param 1	Param 2		Param P	Event Marker	ACR Phase	
	151							
	152	103.40	1		277.40	Rotate	Takeoff	
	153	103.70	1		103.70			
	335	105.13	1		105.13			
	336	105.45	0		105.45	Gear Up		
	337	105.73	0		105.73			
							climb	
	1225	106.82	0		106.82			
	1226	107.89	0		107.89	10000 ft AFE		
	1227	108.10	0		108.07			
	3236	108.51	0		109.04			
	3237	109.33	0	1	109.12	Max Altitude	Cruise	
	3238	110.25	9		109.74			
	6259	109.04	/0		108.60			
	6260	100	0		109.57	10000 ft AFE		
	6261		0		110.39			
		- 41: l- 4					Approach	
	e.g.; thes	e nignt	0		110.53			
_	gments co	nmhine	to 0		110.68	Gear Down		
	•		1.		111.29			
	form the "	Cruise'	,					
			1		112.10		Landing	
	phas)1		112.43	Touchdown			
			1		112.90			

Analysis

Step 10: Cluster the Transformed Signatures

- Use several alternative clustering methods
 - Then, generate an ensemble
- Typical patterns
 - Clusters of similar flights
 - Summarized in plain English
- Atypical flights
 - Singletons, clusters of 1 or 2
 - Summarized in plain English
- Performed for each user-defined and selected flight phase



Analysis

Step 11: Find the Atypical Flights

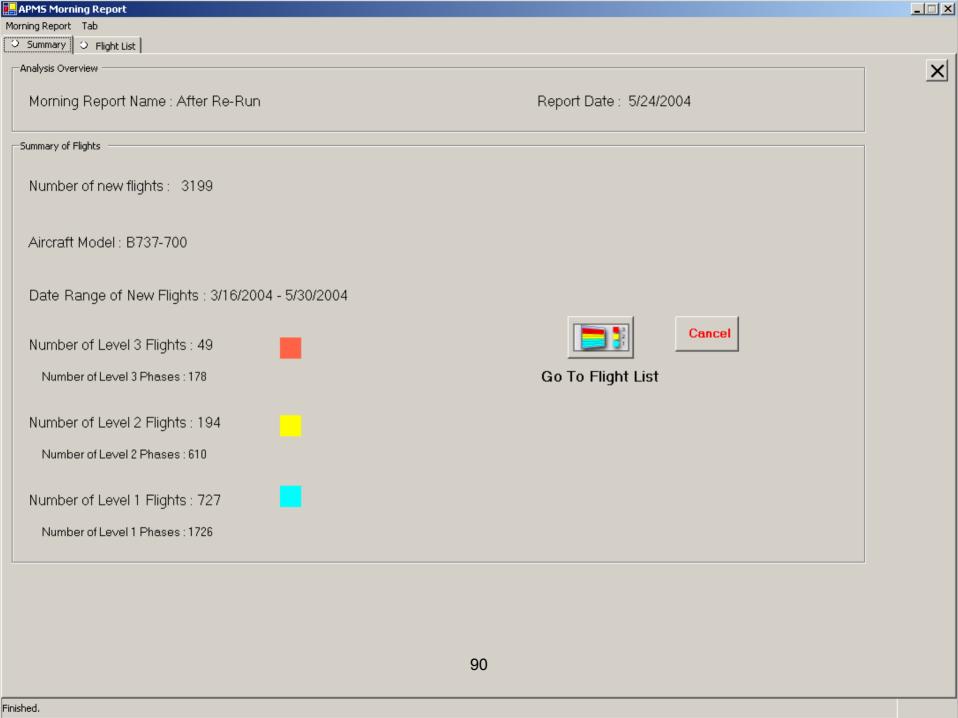
- Atypical flights are defined to be
 - Singletons
 - Very small clusters (atypical clusters)
- Differs from classic exceedance analysis
 - Which look for parameter values outside of <u>pre-defined</u> ranges within a flight phase
- Can be the impetus for further investigation
 - By operationally knowledgeable persons

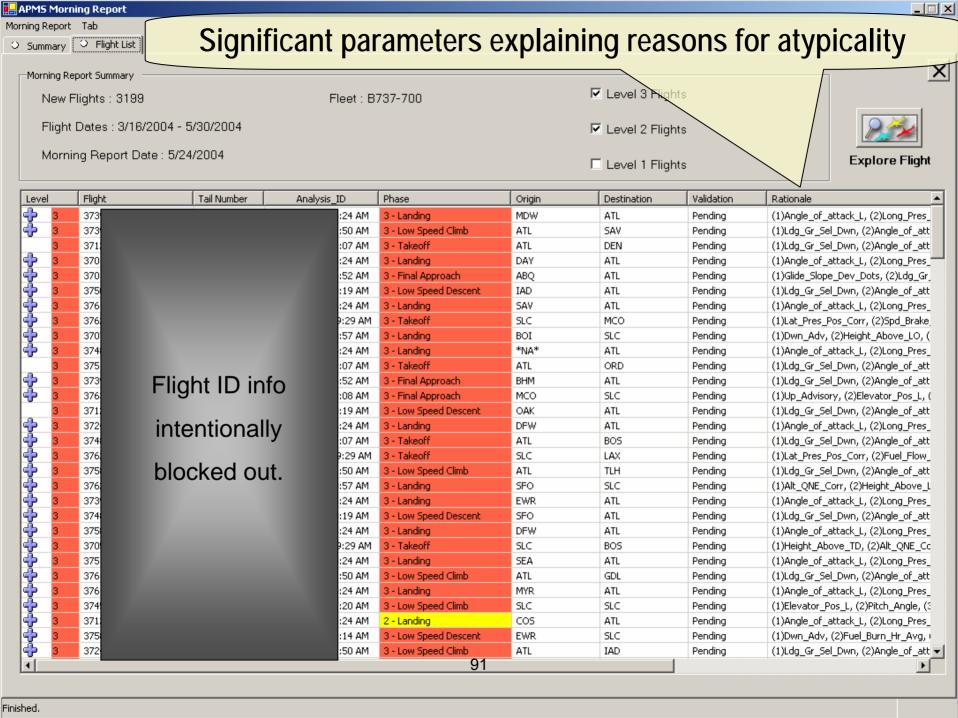
Finds the unenvisioned!!

End-users don't have to know what they are looking for !!

Step 12: Present the Findings

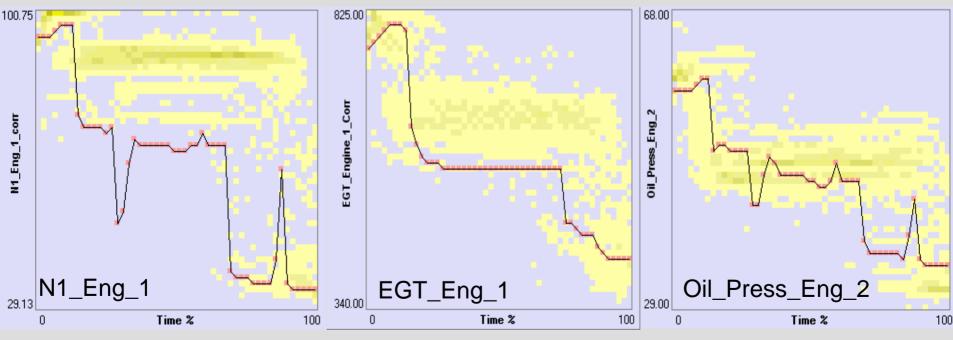
- Data processing occurs over night
- Morning report is ready by 7am every morning.
- Identifies most atypical flights
 - Excludes flights previously reviewed and dispositioned
 - Enables drill down to flight details
 - Allows capture images in Microsoft PowerPoint files for communication ease





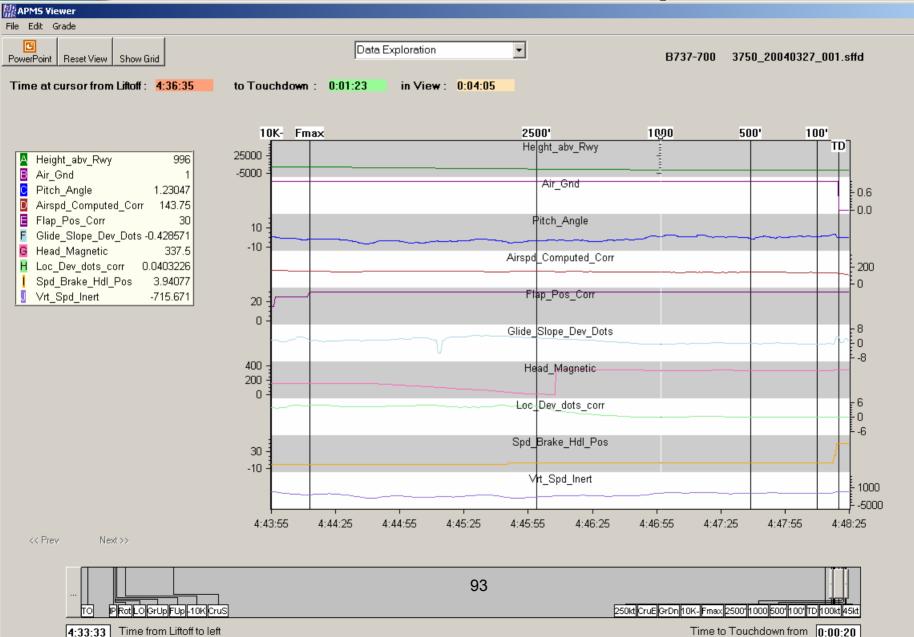
Atypical Flight Rationale Example

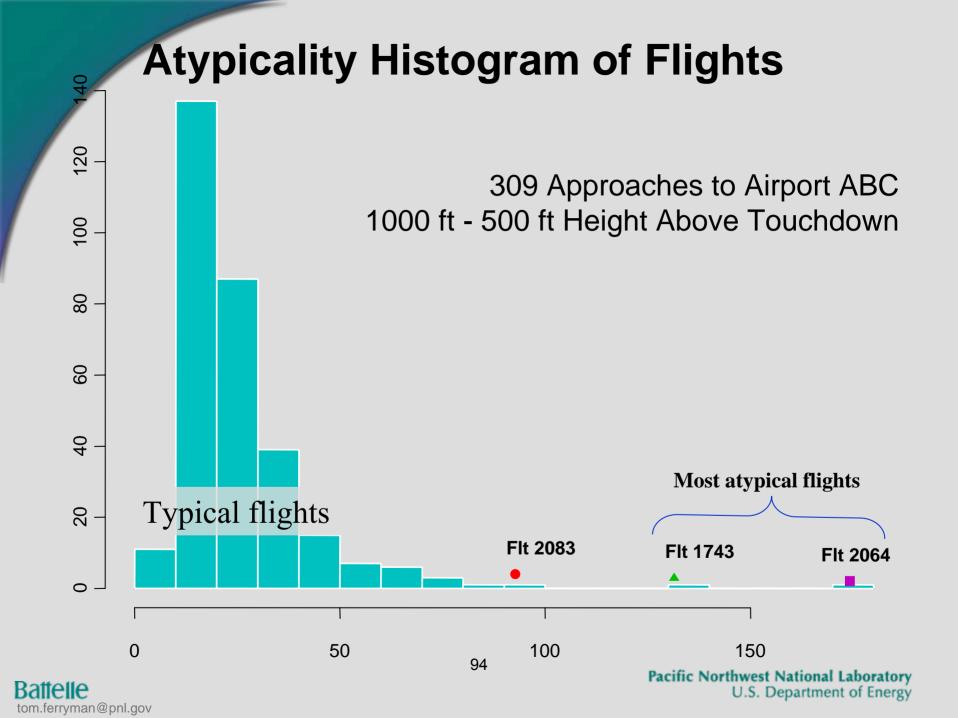
N1_Eng_1 on average is lower than normal during Cruise. EGT_Engine_1 on average is cooler than normal during Cruise. Oil_Press_Eng_2 is noisier than normal during Cruise.



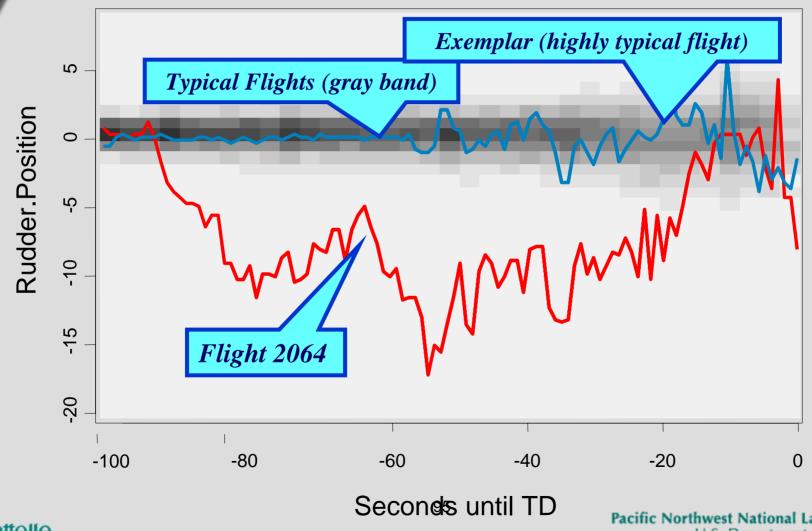


APMS Viewer Example





What made Flight 2064 Atypical?





Pacific Northwest National Laboratory U.S. Department of Energy

Profiler Tools

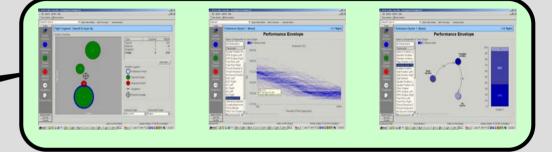


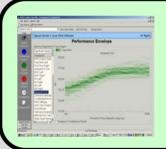
User defines the investigation

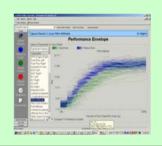
Computer analyzes the data; Provides an overview of results

Clusters are examined and compared

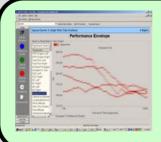
Atypical clusters and singletons are examined

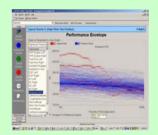








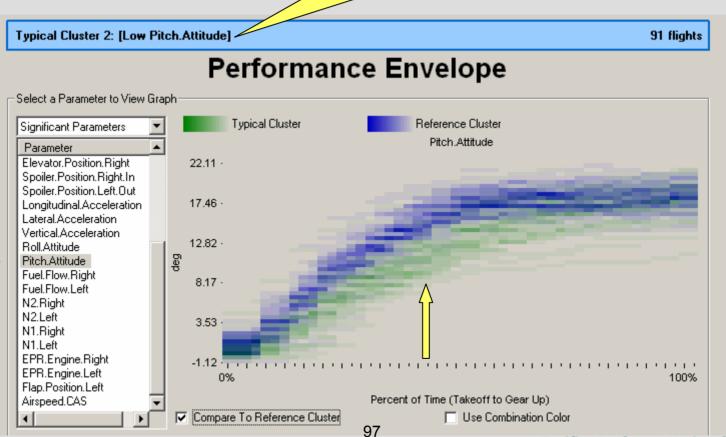






Cluster Comparison



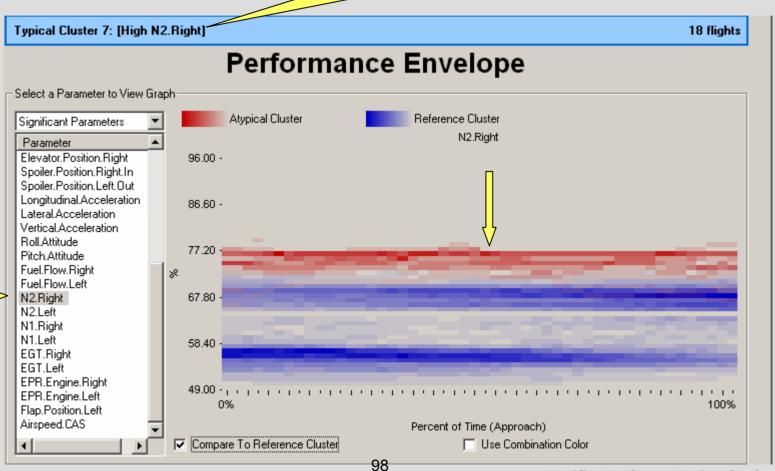




Pacific Northwest National Laboratory
U.S. Department of Energy

Atypical Cluster Performance Envelope

Automated cluster label





Pacific Northwest National Laboratory U.S. Department of Energy

Storymeister Example

- Cluster 8 contains 18 flights. It has highly unusual values in the engine parameter set during the 5000 ft to 2500 ft approach phase. It also has moderately unusual values in the flight controls parameter set during this phase.
- Cluster 8 has extremely large N1.Left (mean value of 96 PCT) and N1.Right (mean value of 97.1 PCT) values during the 5000 ft to 2500 ft approach phase. It also has unusually low flap.position.left (mean value of 3 degrees) values and extremely high noise in Airspeed.CAS (mean noise of 1.5 knots). The Rudder.Position rate of change was moderately high (mean rate of change of 0.25 degrees).

In Summary

- ► The Morning Report uses:
 - Multivariate statistical analysis and
 - User-friendly software

To enable the user to understand:

- Typical patterns observed in the operation of 1000s of flights
- Atypical events
- Identify flights and their flight characteristics associated with safety issues
- Share the information with a community of aviation experts, thus enabling them to formulate improve aviation policies and action plans.



A very important characteristic: The Morning Report is extendable to numerous other domains.

- ► Areas in work
 - Air traffic control
 - Electric Power Grid
 - Cyber Security
 - Intelligent Vehicle Health Monitoring
- Areas that have been or currently are being discussed
 - NASA mission monitoring
 - Automobile warrantee monitoring

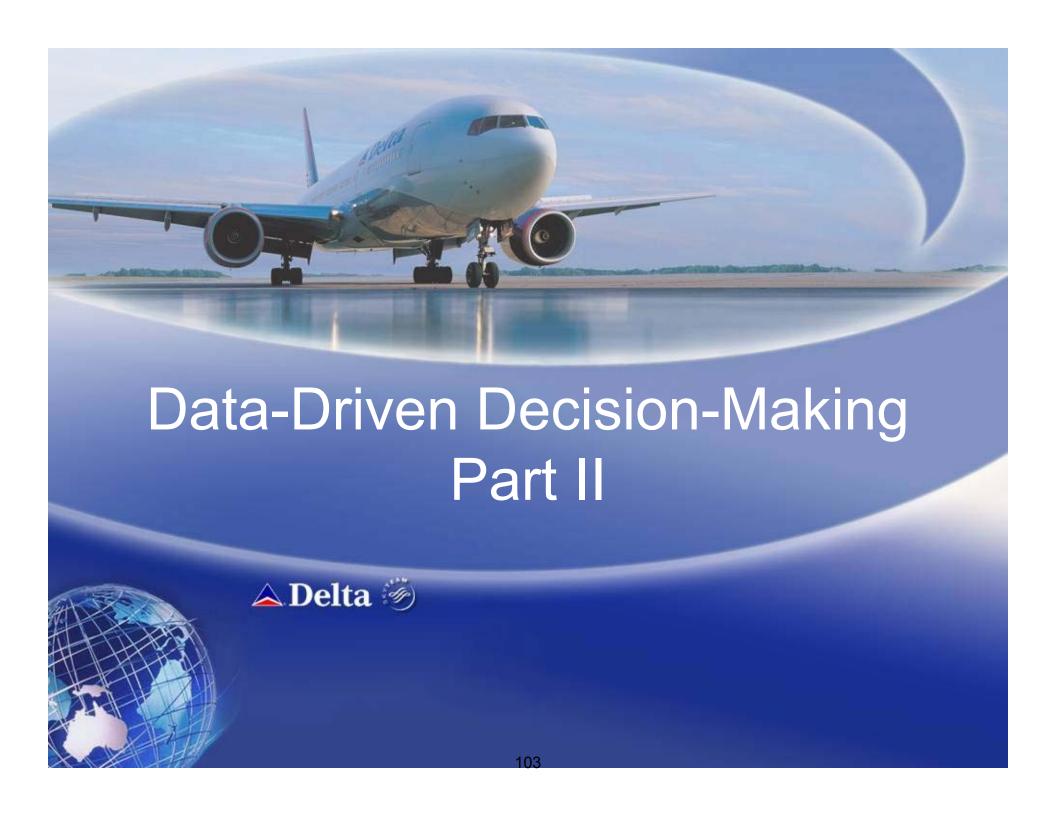


Data-Driven Decision-Making

Michael New Delta Air Lines, Inc.

Michael New began his aviation career in the US Air Force as a fighter pilot (F-15), instructor, and evaluator. During his tour in the Air Force, he served as the Chief of Mobility, Chief of Training, and the Chief of Standardization and Evaluation for various units. He holds a Ph.D. from the Georgia Institute of Technology in Human Factors Engineering and has served as a consultant for the US Navy, NASA, and Lockheed-Martin. As a member of the National Safety Committee for the Airline Pilots' Association, Mike conducted research and aircraft accident investigations. Beginning in 2002, Mike served as General Manager of the Research and Development Group within Delta Air Lines. In this role, he managed the Continuing Education, Advanced Qualification, and Curriculum Development functions for Flight Operations.

Currently, Mike is a B-737-800 Captain and the Director of Flight Safety for Delta Air Lines. As the flight safety leader for the third largest airline, he has implemented one of the first cross-divisional Safety Management Systems at a US carrier and is responsible for all accident/incident investigation, data collection/analysis, and aviation-related research. In addition to his duties at Delta, he serves on the Safety Council (ATA), the Human Factors Working Group of the Performance-based Operations Aviation Rulemaking Committee (FAA), and the Automation Working Group for the Commercial Aviation Safety Team (FAA). Mike has presented at national and international conferences, co-chaired one international conference (LOSA/TEM), and advised leaders within governmental, industrial, and labor organizations.



Overview: Data-Driven Decisions



Review from Last Year:

- Safety Management System (SMS):
 - Harmonized taxonomy and data collection process.
 - Safety Round Table (SRT).
- Contributing philosophies:
 - Six-sigma (continuous improvement).
 - Threat and error management.
 - Statistical Process Control (SPC) charts.

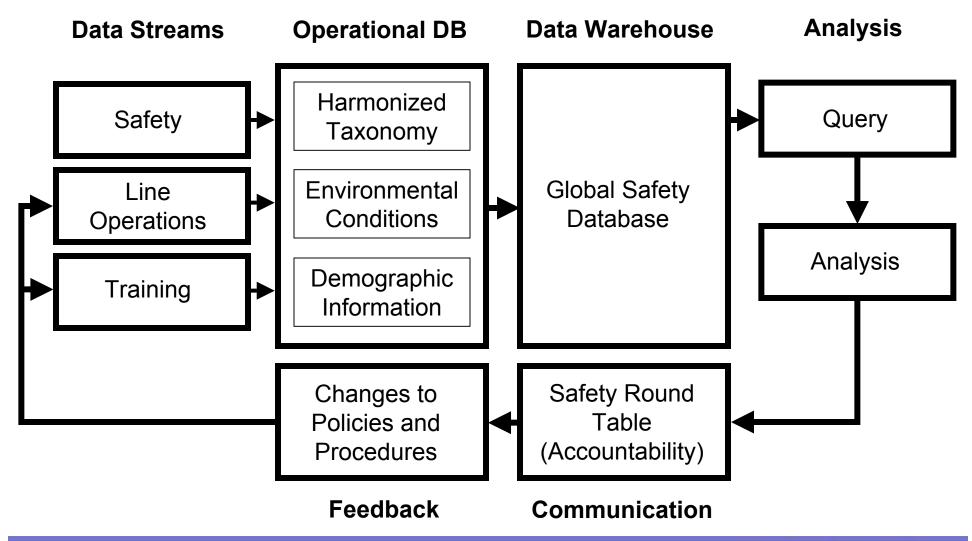
Latest Innovations:

- Score cards.
- Aviation Safety Action Program (ASAP).
- Concept-mining.



Safety Management System







Six-Sigma: Key Concepts



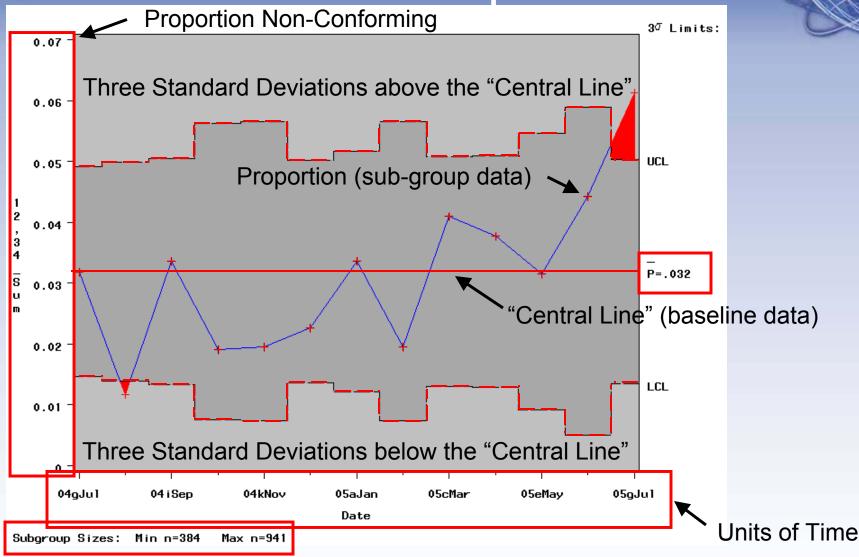
- Goal: Boost safety by improving quality.
- Quality: Providing the "right features" while eliminating "defects."
- Continuous Improvement: A management strategy based on measurement and analysis of relevant data that leads to positive change.

Statistical Process Control Charts

- Used to monitor processes for excessive variation.
- Why keep a process in control?
 - Prevention of negative change (i.e., departure from standards).
 - Maintains current levels of performance Predictability.
 - Necessary prerequisite to improvement:
 - If not in control, it's impossible to know if the changes being made are responsible for the observed effect.



SPC: General Description





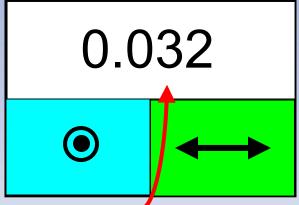
Scorecard Overview...

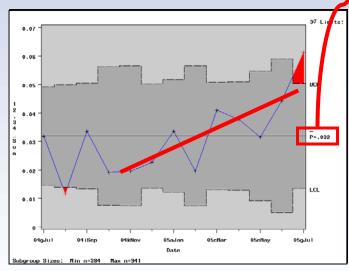
0	Positive trend for this fleet.
•	Negative trend for this fleet.
\leftrightarrow	Best performer for this task.
\rightarrow	Worst performer for this tack

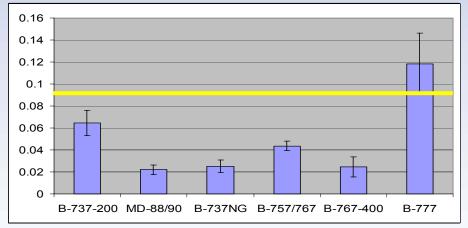
Task	Task Average	732	M88	73N	767	764	777
Qual MV	0.082	0.108	0.051	0.013	0.148	0.142	0.032
				\leftrightarrow			
Qual LOE	0.077	0.118	0.040	0.093	0.088	0.113	0.013
732 [M]; 73N [M]	0.077	•		•			
CQ MV	0.056	0.068	0.035	0.044	0.092	0.076	0.023
	0.056				\leftrightarrow		
CQ LOE	0.037	0.035	0.020	0.033	0.040	0.054	0.039
	0.037		\leftrightarrow				
Total	0.054	0.061	0.030	0.039	0.073	0.074	0.028
	0.051						
Fleet Average	0.063	0.082	0.037	0.046	0.092	0.096	0.027

Score Card Box Explained...











Scorecard Overview...

- Positive trend for this fleet.
- Negative trend for this fleet.
- Best performer for this task.
- → Worst performer for this task.

	Task	Task Average	732	M88	73N	767	764	777
	Qual MV		0.108	0.051	0.013	0.148	0.142	0.032
		0.082			\leftrightarrow			
	Qual LOE	0.077	0.118	0.040	0.093	0.088	0.113	0.013
	732 [M]: 73N [M]		9					
Requested response to scorecard findings.		0.056	0.068	0.035	0.044	0.092	0.076	0.023
						\leftrightarrow		
		g.037	0.035	0.020	0.033	0.04	0.054	0.039
				\longleftrightarrow				
	Total	0.051	0.061	0.030	0.039	0.073	0.074	0.028
	Fleet Average	0.063	0.082	0.037	0.046	0.092	0.096	0.027

Trend information for this task on this fleet. Red indicates a "lack of control." Comparison with other fleets.

July - September 05



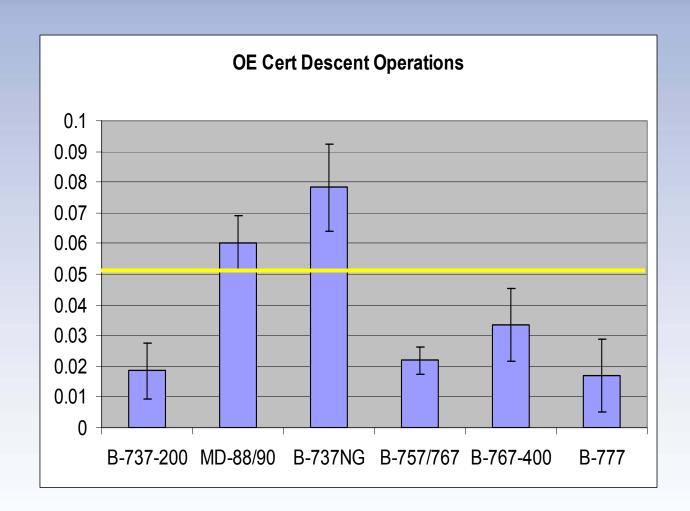
Example: Qual OE Cert (SRT Oct. 2005)

Task	Task Average	732	M88	73N	767	764	777
Ground Operations	0.010	0.000	0.014	0.017	0.008	0.013	0.008
	0.010	\leftrightarrow		⊙			
Takeoff Operations	0.011	0.000	0.010	0.008	0.005	0.000	0.042
777 [A]	0.011	\leftrightarrow				\leftrightarrow	\leftrightarrow
Climb Operations	0.010	0.000	0.016	0.022	0.012	0.008	0.000
	0.010	\leftrightarrow					\leftrightarrow
Cruise Operations	0.015	0.014	0.015	0.006	0.015	0.013	0.025
	0.013						
Descent Operations	0.038	0.018	0.060	0.078	0.022	0.033	0.017
M88 [A]; 73N [A]	0.036		\leftrightarrow	\leftrightarrow			
Approach Operations	0.033	0.041	0.043	0.049	0.026	0.029	0.008
	0.033						\leftrightarrow
Landing Operations	0.044	0.028	0.070	0.064	0.037	0.042	0.025
	0.044						
After Landing Operations	0.011	0.009	0.021	0.025	0.010	0.000	0.000
			\leftrightarrow	\longleftrightarrow		\leftrightarrow	\leftrightarrow
Fleet Average		0.014	0.031	0.034	0.017	0.017	0.016



Qual OE Cert Descent Ops





Example: Qual OE Cert (SRT Jan. 2006)

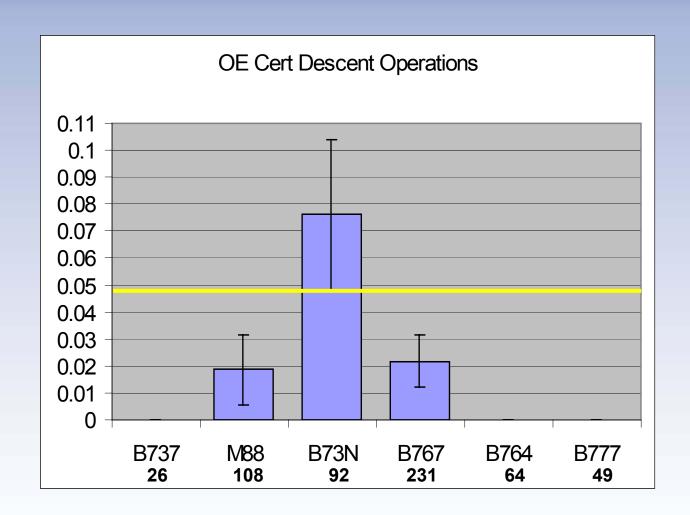
Task	Task Average	732	M88	73N	767	764	777
Ground Operations	0.004	0.000	0.009	0.011	0.004	0.000	0.000
	0.004						
Takeoff Operations	0.009	0.000	0.018	0.033	0.004	0.000	0.000
Climb Operations	0.010	0.000	0.019	0.043	0.000	0.000	0.000
	0.010						
Cruise Operations	0.007	0.000	0.009	0.011	0.022	0.000	0.000
	0.007						
Descent Operations	0.019	0.000	0.019	0.076	0.022	0.000	0.000
73N [A] repeat	0.015			\leftrightarrow			
Approach Operations	0.034	0.000	0.074	0.065	0.026	0.016	0.020
	0.054						
Landing Operations	0.042	0.000	0.037	0.087	0.026	0.063	0.041
		\leftrightarrow					
After Landing Operations	0.012	0.000	0.028	0.011	0.013	0.000	0.020
Fleet Average	0.017	0.000	0.027	0.042	0.015	0.010	0.010

October - December 05



Qual OE Cert Descent Ops

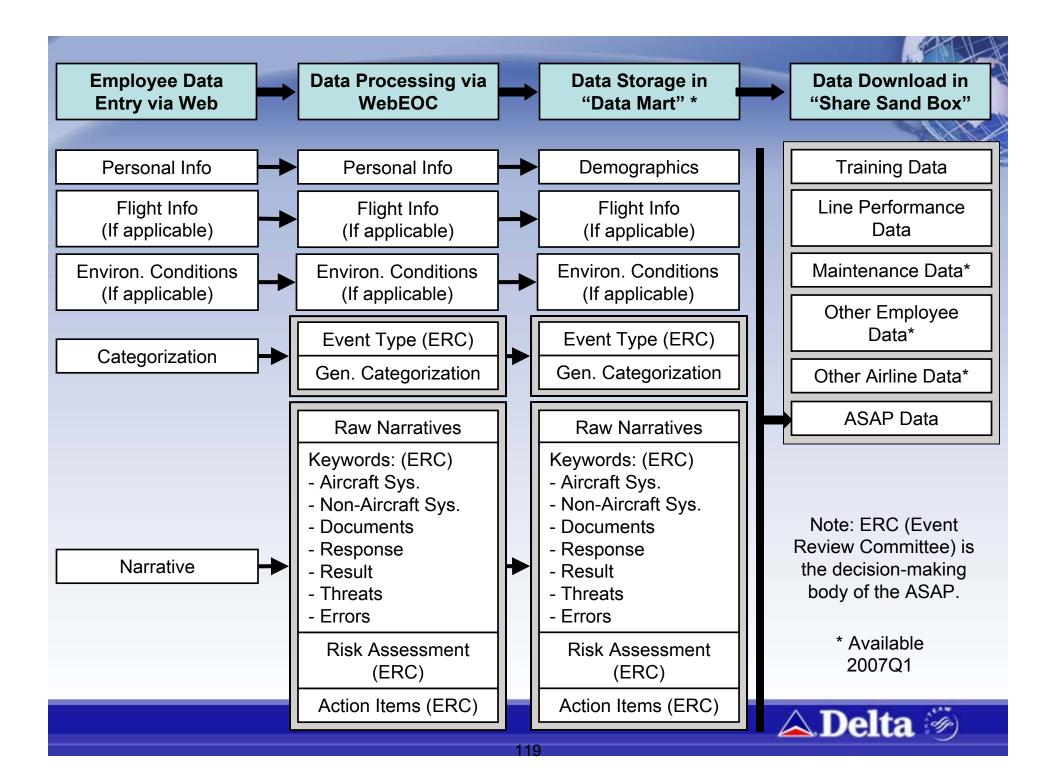




Aviation Safety Action Program (ASAP)

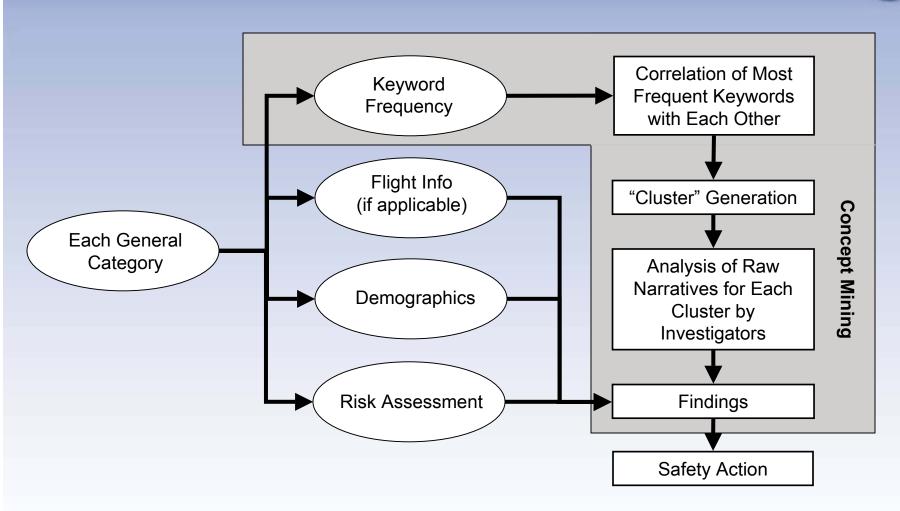
- Goal: To enhance aviation safety through the proactive management of event information that otherwise may not have been available.
- Rewards participation: Allows "FAA enforcement incentives" for participating employees (similar to NASA ASRS).
- Availability: Pilots, dispatchers, mechanics, etc.
- Commitment: Requires the airline and employees to respond to and be accountable for associated correctiveaction recommendations.



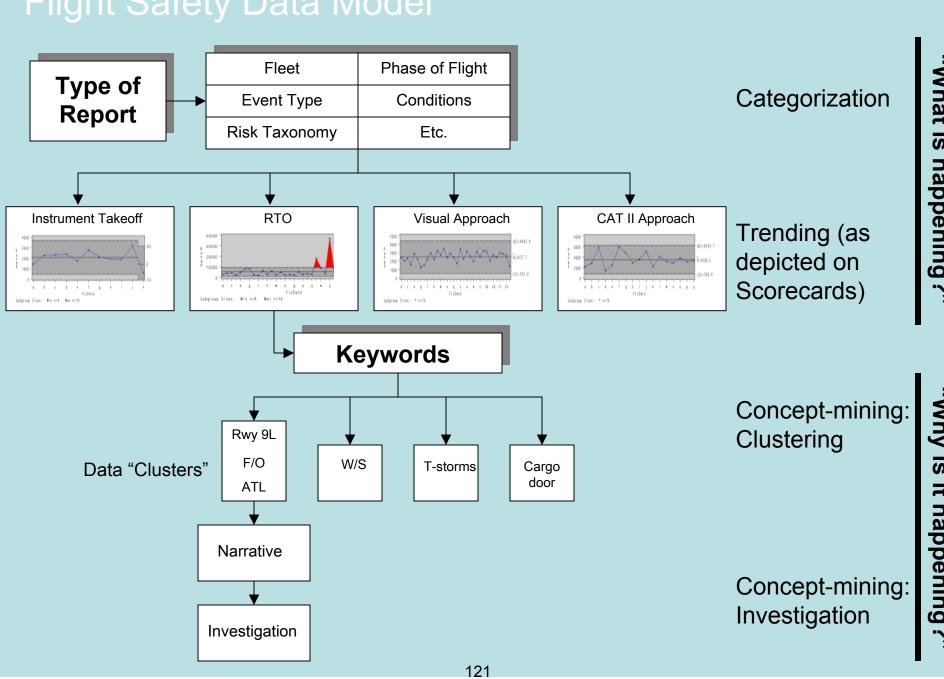


Analysis of Textual Data





Flight Safety Data Model





Institute of Nuclear Plant Operations (INPO) Analysis Activities

Mac Makucin INPO Analysis Institute Institute of Nuclear Power Operations

Mac Makucin is a Senior Evaluator for the Institute of Nuclear Power Operations functioning as an analyst in support of INPO's Analysis Initiative. Analysis is a Centerstone for INPO programs, characterized by:

- Innovative predictive modeling and forecasting techniques that enable INPO to predict and shape industry performance.
- Identification of plants susceptible to extended shutdown in time to avoid further significant performance decline.
- A further ten-fold reduction in the number of significant events to be realized by 2008.
- Timely and insightful analysis, permitting more effective and efficient evaluation, assistance, and accreditation activities.

Mac has experience as a nuclear power plant evaluator in the areas of Engineering, Operations, Training, and Accreditation. He has managed nuclear power plant engineering and training organizations and has held a Senior Reactor Operator Certification on a General Electric boiling water reactor plant. Mac holds a Bachelor of Science degree in Nuclear Engineering and Masters of Science degrees in Mechanical Engineering, Electrical Engineering, and Business Administration from Rensselaer Polytechnic Institute.

Institute of Nuclear Plant Operations (INPO) Analysis Activities

Mac Makucin (770) 644-8692 makucinjm@inpo.org

Institute of Nuclear Power Operations (INPO)

Located in Atlanta, Georgia

- Formed in 1980 after TMI
- Promote nuclear plant safety and reliability
- All US nuclear utilities
- Nuclear suppliers
- International members







Analysis Initiative - 2002

Davis-Besse Head Wastage Lessons Learned

- Improve INPO's analytical capability
- Better predict future plant performance and detect emerging industry trends
 - Dedicated team of analysts
 - Specialized software (SAS)
 - Industry involvement
 - Good data sources (*clean data*)
- Benchmark other industries

Analytical Tools

Station Performance Monitor (Real time)

Summary report (event roll-up)

Data Mining (One Year Look Ahead)

Predictive tools for declining performance

Text Miner (Look back from months to years)

- Plant-specific analysis
- Identify industry issues and trends

Station Performance Monitor

- Plant events reviewed DAILY
- Point system scores events in real-time
- Points accumulate and expire periodically
 - Currently 6-month rolling average
 - In local database to preserve "memory"

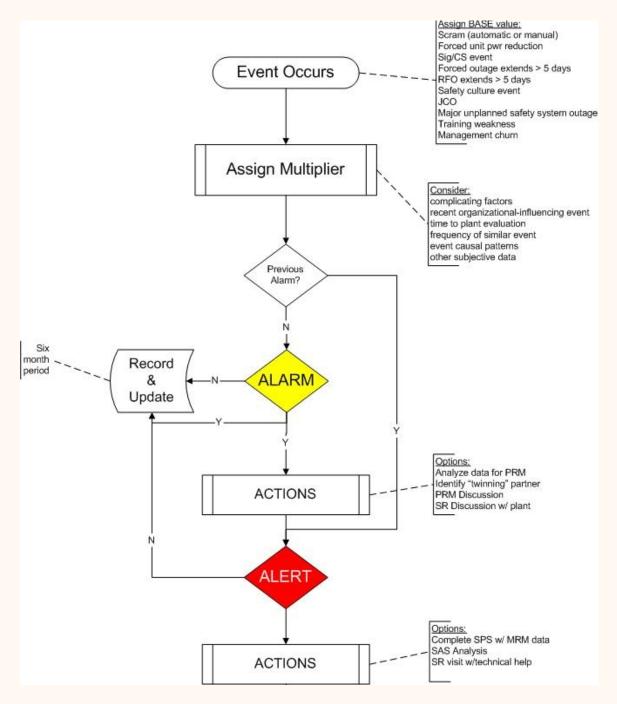
Event Categories

- ACTUAL performance events (safety or generation)
 - Scram (automatic & manual)
 - Unscheduled power reductions, outages, or outage extensions
 - Significant events, with points differentiating between Nuclear Safety, Equipment Reliability, Radiological Safety, and Personnel Safety
- Potential performance events (organizational behavior)
 - Conditionally significant event
 - Noteworthy event tagged with Safety Culture or Operational Decisionmaking tag
 - Other subjective items

SPM

Process

Chart



Predictive Tools



- Define Declining Performance
 - Extended shutdown... $\Delta PE = -2$... Signif. + NW > 15... ??
- Select inputs
 - Plant Evaluation results
 - Industry Performance Indicators
 - Significant + NW events
 - Time to First Forced Shutdown
 - Management changes
 - Labor issues
 - Others...
- Apply analysis tools

Extended Shutdown Tool

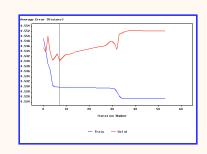
- Predicts susceptibility to an extended shutdown (this is a rare event in the nuclear industry)
- Examines plant performance indicators
 - Identifies plants that have similar performance to previous plants just prior to entering an extended shutdown
 - Assistance is provided to the plants as needed to address the problem areas
 - Currently, no identified plants have suffered an extended shutdown

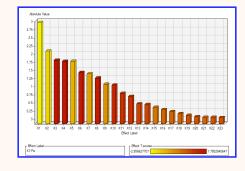


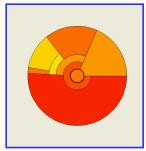
Predictive Modeling

Three-pronged analysis

- Regression
- Decision Trees
- Neural Network



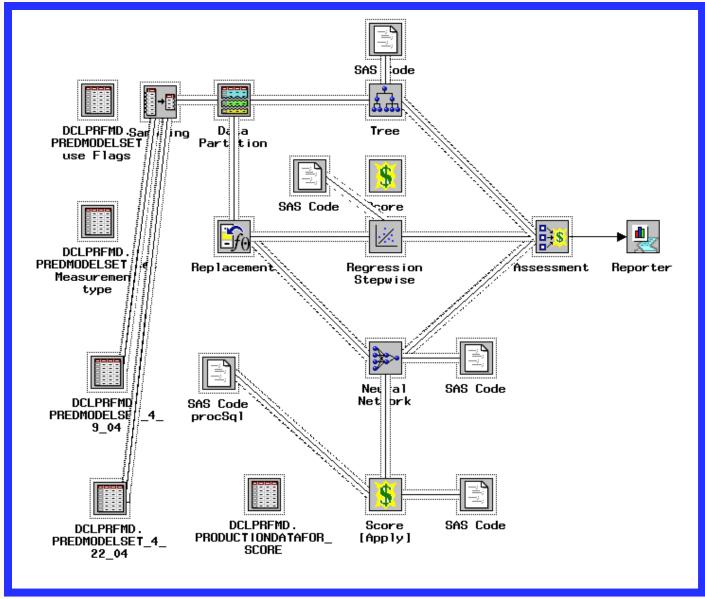




Predicts a drop <u>into</u> the bottom quartile of the **Performance Indicator Index** a year in advance.



Predictive Model





Model Accuracy

Prediction period: 2003 – 2004

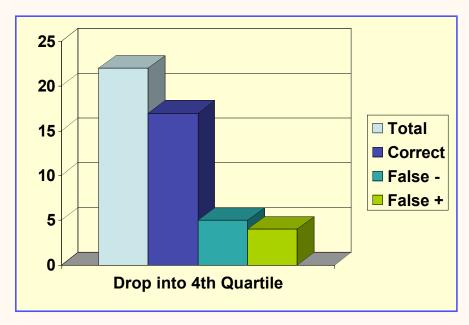
Plants that fell into 4th quartile: 22

Plants correctly predicted: 17 of 22

False positives: 4

False negatives: 5

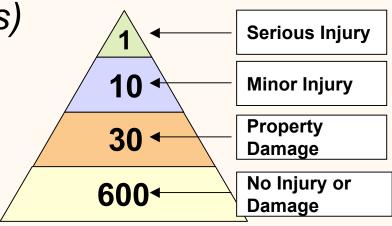






Text Miner Projects

- Plant-specific analysis
 - aid the pre-evaluation team
- Identify industry issues and trends
 - Industry events clustering
 - Industry trending (Mine CAP databases)





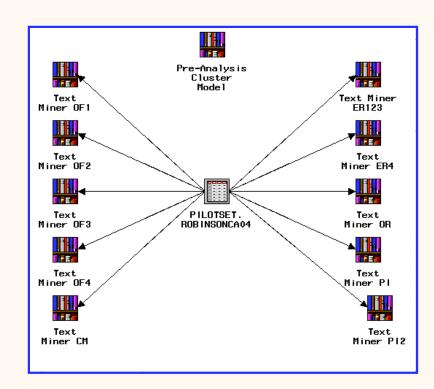
Plant-Specific Analysis

Used *filtered clustering* to identify *Condition*Reports that related to evaluation criteria

- Start Lists
- Synonym Lists
- Outputs

Success achieved if:

- Review and tag more
- Identify high value
- Do it faster





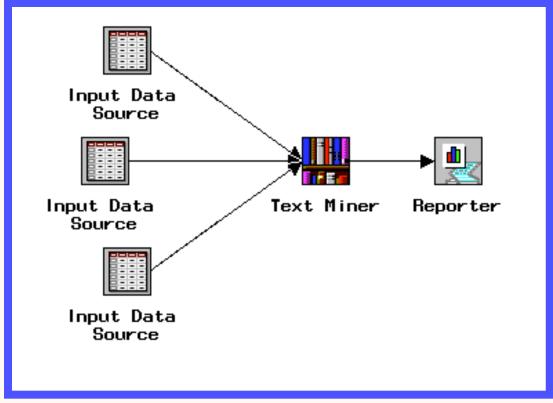
Events Clustering

- Perform unfiltered clustering of industry & regulatory reports with text miner
 - Blind clustering
 - No preconceived notions
- Identify emerging industry trends
- Communicate results
 - OE Digest



Industry Trending

- Multiple plant databases
- Perform unfiltered clustering with text miner
- Identify emerging industry trends



Challenges

- New skills for our work force
- Learning the software (not intuitive)
- Accuracy of results (a culture shift)
- Reliable data (always a challenge)
- Pushing the envelope on the software

Questions?

Institute of Nuclear Plant Operations (INPO) Analysis Activities

Mac Makucin (770) 644-8692 makucinjm@inpo.org

Data Acquisition

- Regulatory required reports are reviewed daily.
- All stations report performance indicator numerical data and equipment performance information every quarter.
- Noteworthy level events are reported within 60 days of occurrence.
- Lower level corrective action program items are submitted every two years.

Data Validation

- Submission software rejects format and obvious data errors until corrected.
- Technical personnel review all reported information and apply various coding criteria to support trending.
- If clarification is required, additional information is obtained from designated station contacts.

Data Preparation

- Quarterly, selected numerical data is manually transferred into existing SAS data files to update the files for predictive modeling.
- Text data (regulatory reports, event reports, and corrective action reports) are stored on designated drives for the SAS Text Miner.

Date:05-05-2006

Subject:OE22550 - Update to OE22423, Unit 1 Manually Tripped due to Main Feed Water Regulating Valve (MFRV) Failure

Abstract:

On April 15 2006, while at 100% power the Unit 1 Control Room crew was challenged by erratic response of the loop 3 MFRV. The crew was able to stabilize the valve in manual mode, however, over the next 24 hours the control of the valve continued to degrade. On April 16 2006, it was decided Unit 1 would be taken to Mode 3 for investigation of the issues with Loop 3 MFRV. On April 17 2006, Unit 1 was manually tripped at 33% RTP due to the loop 3 MFRV not controlling Steam Generator water level in auto or manual.

Reason for Message:

To provide updated information on the 4/17/06 Unit 1 manual reactor trip investigation associated with the use of Masoneilan model 7000 current to pressure (I/P) transducers on plant air operated control valves. Failures of Masoneilan 7000 I/P transducers have lead to unreliable equipment operation which resulted in unavailable equipment and reactor trips.

Event Date: 04/17/06

Description:

The Masoneilan 7000 I/P transducer is the replacement transducer for the obsolete Masoneilan model 9000 I/P transducer. The Masoneilan 9000 I/P transducer has been a very reliable I/P, which offered a tight shutoff feature not available from other manufacturers. The tight shutoff feature reduces the I/P output pressure to zero psig once the input current drops below the adjustable setpoint. utilized the tight shutoff feature to ensure I/P or positioner calibration drift did not cause valve leakage.

The Masoneilan 7000 was the replacement for the model 9000 and also has the tight shutoff feature. The Masoneilan 7000 was first evaluated 1999 in the Steam Generator Blowdown System (SGBD) and during use as a test I/P transducer during AOV diagnostic testing. Through testing and use in the SGBD system, the I/P's were determined to be reliable.

In 2001 a change was noticed in the performance of the model 7000 transducers. Spikes in I/P graph were noticed on all new model 7000 transducers during diagnostic testing, however these spikes did not cause erratic valve operation and were not visible on the valve graphs. The vendor performed a root cause analysis on the spikes and determined that it was normal for a model 7000 I/P with a small volume of air on the outlet. The larger the outlet volume the smaller the spikes introduced by the cycling of the Reedex valve became. continued to use the model 7000, and over the next 3 plus years no additional problems were noted.

In August 2005, a model 7000 was installed on the RHR Heat Exchanger discharge valve due to a drift issue on the previous model Fisher 546 I/P transducer. When attempting to stroke this valve in September 2005 the valve would not fully close. A replacement model 7000 I/P was installed, calibrated and then failed after the cover was installed. An investigation found the supply air connector for the internal Reedex valve was positioned over a circuit board capacitor and when the cover was installed pressure was applied to the supply air connector resulting in a crack. This crack limited the supply to the Reedex and caused the I/P transducer not to be able to obtain full output.

Masoneilan was contacted and the defective I/P transducer returned. Masoneilan's corrective actions addressed the manufacturing method for the drying process of the Reedex valve. Masoneilan's corrective actions did not address the issue of the Reedex supply air connection being over the circuit board capacitor. One of Plant correction actions was to inspect the Masoneilan 7000 I/P transducers installed in the plant and the remaining warehouse stock for proper positioning of the Reedex valve supply air connector (connector not positioned over the circuit board capacitor). During the inspection of the remaining stock, only one of seven remaining warehouse stock was found to be acceptable. The inspection of the installed I/P transducer in the plant found all I/P's to be acceptable or tubing was modified to prevent contact with the capacitor on the circuit board.

Additional Masoneilan 7000 failures have occurred, one of which resulted in a reactor trip when the Unit 1 loop 3 MFRV stopped responding to input signals. This I/P failed due to moisture intrusion. The I/P had been installed upside down, and when the area near it was washed down, water entered through a vent hole and the circuit later failed. Contributing to this also, it is believed that the internal circuit coating over the board was not adequate. During the Unit 1 reactor start-up another Masoneilan 7000 failed on the heater drain tank high level dump AOV. Because the decision to replace all model 7000 I/P's on the plant site had already been made additional root cause testing was not performed on the heater drain tank I/P.

Causes:

Significant manufacturing changes were made that did not change the model number, outline drawing, installation and operating manual, or otherwise trigger the need for an engineering evaluation have lead to equipment reliability problems with Masoneilan model 7000 I/P transducers. These transducers are non-safety related and not in the equipment qualification program.

Corrective Actions:

Based on the repeated failures and decreasing component reliability of the Masoneilan model 7000 I/P transducers, Plant will be replacing all the Masoneilan 7000 I/P transducers installed in the plant and will discontinue their use.

Safety Significance:

Even though the I/P transducers at Plant are non-safety related, their failures can initiate an upset condition that challenges safety-related equipment and cause plant transients including reactor trips.

Predictive Modeling

- Every quarter, selected data is run through previously developed predictive models to forecast target variables such as plant assessment decline and degraded performance.
- Every quarter, predictive model accuracy is graded by comparing the actual data against the prediction from last year.

Text Mining

- Every month, separate text mining is conducted on regulatory reports, event reports, and several station corrective action databases.
- The results of the text mining is many clusters of documents, each with a common theme as determined by the software.

Example Text Mining

Text mining produced the following 11 clusters of eight words:

- 1. admin, control, documentation, error, human, process, schedule, procedure (1113)
- 2. design, engineer, leak, valve, water, repair, inspection, standby (826)
- 3. leak, motor, pump, water, wear, maintenance, hydraulic, contact (735)
- 4. annunciator, calibration, instrument, limit, monitor, staff, engineer, electrical (727)
- 5. breaker, contact, electrical, scram, motor, switch, annunciator, maintenance (445)
- 6. chemistry, sample, storage, tool, water, control, monitor, reactor (434)
- 7. confine, emergency, fire, industrial safety, injury, protective, safe, safety (342)
- 8. annunciator, barrier, emergency, fire, design, program, engineer, pump (328)
- 9. admin, drill, emergency, human, program, simulator, train, error (303)
- 10. air, diesel, generator, standby, switch, emergency, valve, design (232)
- 11. core, hydraulic, reactivity, reactor, rod, limit, scram, monitor (141)

Example Text Mining

The line 7 cluster broke down as follows:

- 1. confine, wear, safe, tool, protective, maintenance, emergency, basis (67)
- 2. fire, first aid, human, OSHA, shock, close, admin, safety (65)
- 3. process, tool, confine, protective, safe, wear, water, admin (61)
- 4. water, protective, confine, process, safe, tool, wear, documentation (50)
- 5. documentation, OSHA, human, maintenance, fire, shock, basis, first aid (45)
- 6. tower, water, basis, maintenance, human, first aid, documentation, admin (20)
- 7. light, process, maintenance, safe, confine, protective, tool, wear (17)
- 8. vehicle, admin, close, human, shock, fire, process, injury (17)

Text Mining Analysis

- Technical analysts review the documents contained in each cluster to determine if the grouping is meaningful.
- Many clusters are discarded because the information is not meaningful or has been already identified.
- Clusters with meaningful information must then be further researched to identify an emerging trend.

Identification of Trends

- Tens of documents from a meaningful cluster are read to better determine if an emerging trend exists.
- The analyst attempts to be as specific as possible in stating the adverse trend that is contained in the documents.
- The analyst does not apply any tests for statistical significance to the trend.

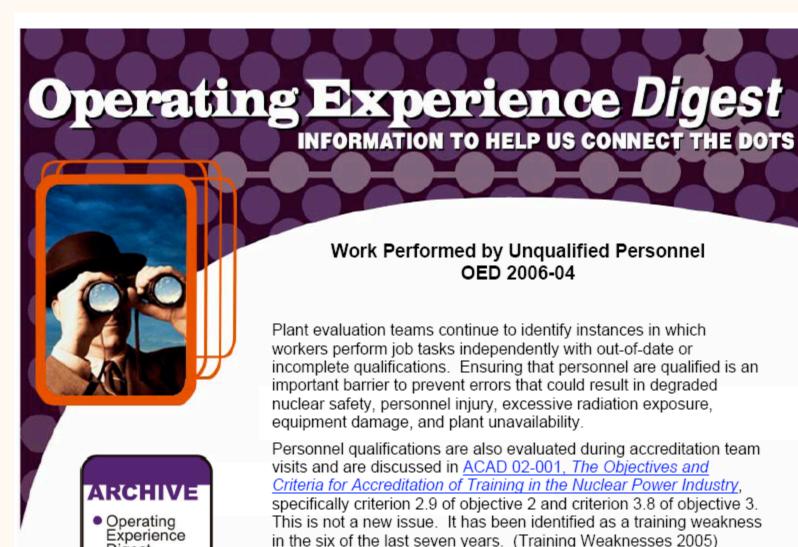
Example Trends

SAS Text Miner – unfiltered clustering	Period & Sources Mined
Emergency Diesel Generator Deficiencies	six months of OE reports
Radiation Exposure & Industrial Safety issues	five months of OE reports & NRC 50.72s
Foreign Material Exclusion issues	three months of OE reports & NRC 50.72s
Control Rod Drive Systems	three months of OE reports & NRC 50.72s
Switchyard & Transmission Line Issues	three months of OE reports & NRC 50.72s
Fire Suppression Systems	three months of OE reports
Safety-related Pumps	four months of OE reports
Vibration Issues	four months of OE reports
Radiological Issues	six months of OE reports
Steam Leaks	four months of OE reports
Refueling Outage Issues	six months of OE reports
Plant Chemistry	six months of CAP data from several plants
Environmental Hazards	two months of CAP data from several plants
Supplemental Personnel Issues	three months of CAP data from several plants
Procedure Issues	three months of CAP data from several plants
Calculations	three months of CAP data from several plants
Vapor Extractors	three years of CAP data from several plants
Operability Issues	six months of CAP data from several plants

Actions

- Correspondence awareness/information
- Operating Experience Digest review/info
- Topical Report review/action
- Significant Event Report review/action
- Significant Operating Experience Report action required/evaluation follow-up

Example Actions



Example Actions

INPO TR2-14, A1 Page 1 of 18

Executive Summary

An adverse trend of events involving supplemental personnel was identified in topical report TR2-14, Review of Events Involving Contractors, and analyzed in INPO 03-002, Analysis of Events Involving Nonstation Personnel. Prompted by industry feedback, supplemental personnel events from the plant events database (PED) from 2003 through 2005 were reviewed and compared to the prior analysis to identify any changes. This analysis revealed continuing adverse trends involving supplemental personnel, primarily in the areas of industrial safety, vendor services, and maintenance. The causal factors are similar in nature to those within the original analysis; therefore this analysis is being issued as an addendum to the original topical report.

The number of supplemental personnel events reported per year almost doubled during the recent three-year period as compared to the yearly average of the prior four years. The total number of events classified by INPO as significant involving supplemental personnel is also trending higher. In 2004 and 2005, nearly 50% of all significant events involved supplemental personnel, although the number of all significant events trended lower. Most supplemental personnel significant events involved industrial safety: personnel were either seriously injured, lives were endangered, or lives were lost. In addition, reliance on off-site vendor services have resulted in significant events such as the catastrophic failure of one station's main transformer (SEN 256, Revision 1) and exceeding another station's licensed thermal limit (OE16521).

Issue Resolution

- Station Operating Experience Review
- Station Corrective Action Program
- Industry Users Group
- Electric Power Research Institute
- INPO Plant Assist Visit
- INPO Review Visit
- INPO Evaluation

Questions?

Web Data Challenges

Eric Colson *Yahoo!*

Abstract: Data produced by Web server logs holds a wealth of information about customer needs, intentions, habits, and cultures. While it is invaluable, Web data poses a number of challenges with respect to data management, analysis, and processing.

In accordance with Yahoo company policy, this presentation is not available for distribution.

Eric Colson is a veteran of business intelligence and data warehousing. He has enabled the strategic use of information for many of the largest data warehouses in the world. He specializes in enterprise information architectures that turn corporate data into strategic assets. He currently manages Business Intelligence for Yahoo's Search & Marketplace business unit.

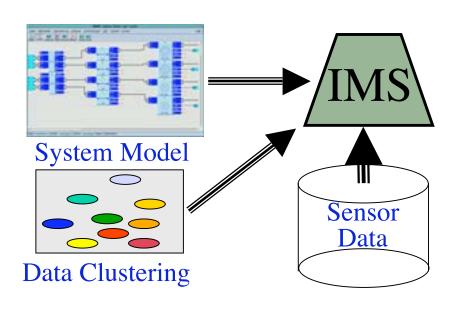
Applications of Clustering for System Health Monitoring

Dave Iverson NASA Ames Research Center

Abstract: Model-based reasoning is a powerful method for performing system monitoring and diagnosis. However, building models for model-based reasoning is often a difficult and time-consuming process. The Inductive Monitoring System (IMS) software was developed to provide a technique to automatically produce health monitoring knowledge bases for systems that are either difficult to model (simulate) with a computer or which require computer models that are too complex to use for real-time monitoring. IMS processes nominal data sets collected either directly from the system or from simulations to build a knowledge base that can be used to detect anomalous behavior in the system. Clustering techniques are used to characterize typical system behavior by extracting general classes of nominal data from archived data sets. IMS is able to monitor the system by comparing real-time operational data with these classes. An overview of the learning and monitoring methods used by IMS will be presented, along with results from several aerospace system health monitoring applications of the tool.

David L. Iverson has been a computer scientist at NASA Ames Research Center since 1985. His research emphasizes application of model-based and machine learning techniques to system fault detection and diagnosis. He is currently project lead for the Ames data analysis effort for the Space Shuttle Wing Leading Edge Impact Detection System. His previous work includes mission control monitoring applications for Shuttle and Space Station, as well as aircraft health monitoring and air traffic management software.

Applications of Clustering for System Health Monitoring



The Inductive Monitoring
System (IMS) combines
features of model based
reasoning and data
clustering to build system
health monitoring
knowledge bases from
archived or simulated
system sensor data.

David Iverson

NASA Ames - Intelligent Systems Division David.L.Iverson@nasa.gov



System Health Monitoring



GOAL:

Provide tools to decrease the workload required to monitor system operation and respond to anomalous behavior



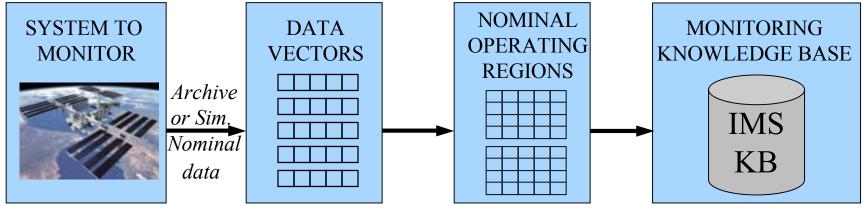


Inductive Monitoring System



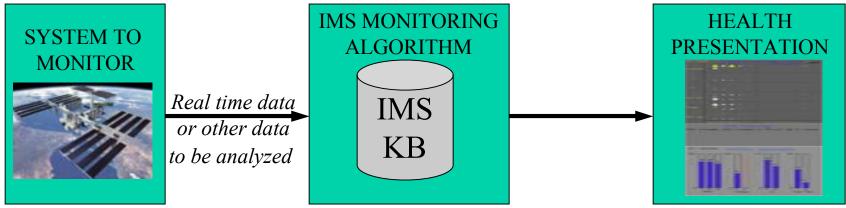
Learns how the system typically behaves and tells you if it is behaving differently now

LEARNING / MODELING



IMS learns nominal system behavior from archived or simulated system data, automatically builds a "model" of nominal operations, and stores it in a knowledge base.

MONITORING

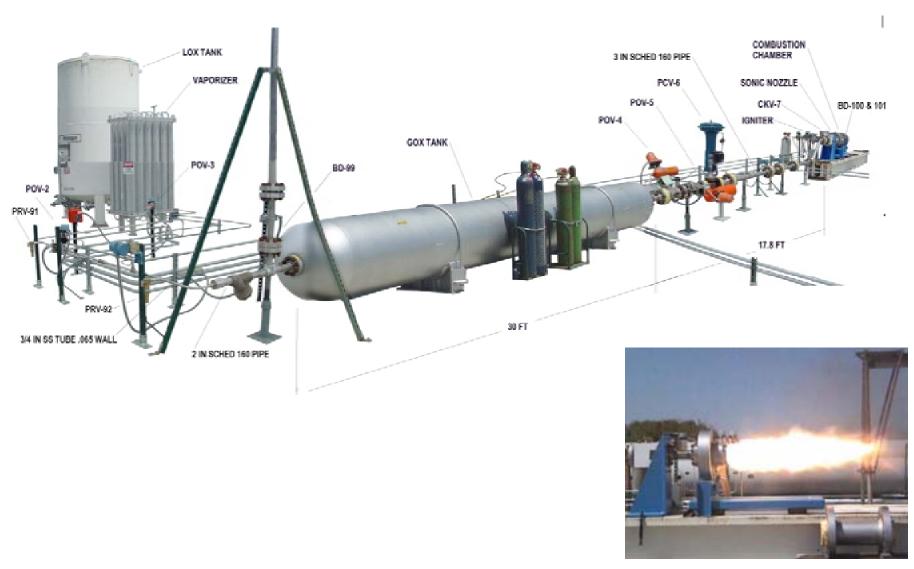


IMS real time monitor & display informs users of degree of deviation from nominal performance. Trend analysis can detect conditions that may indicate an incipient failure or required system maintenance.



Motivation and Example: Hybrid Combustion Facility

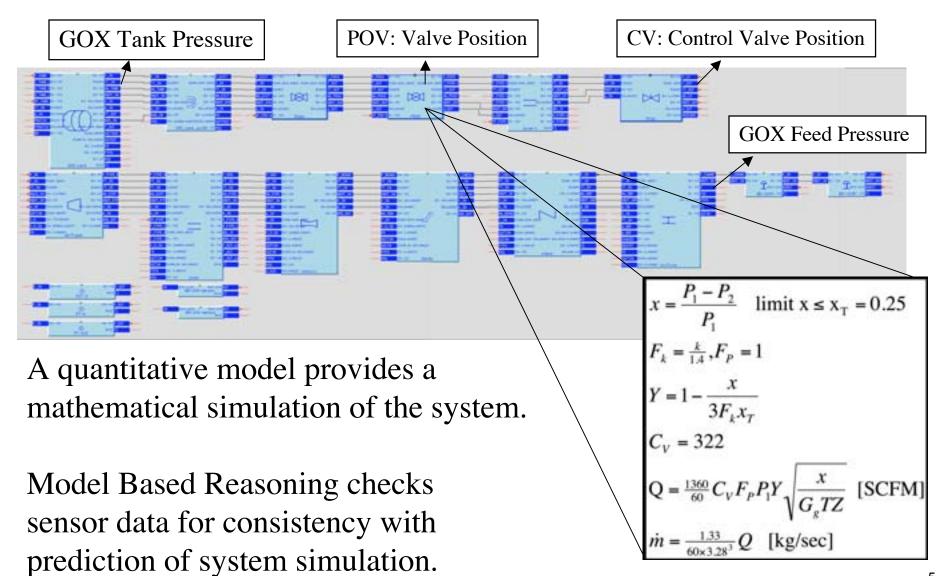






HCF Quantitative Model

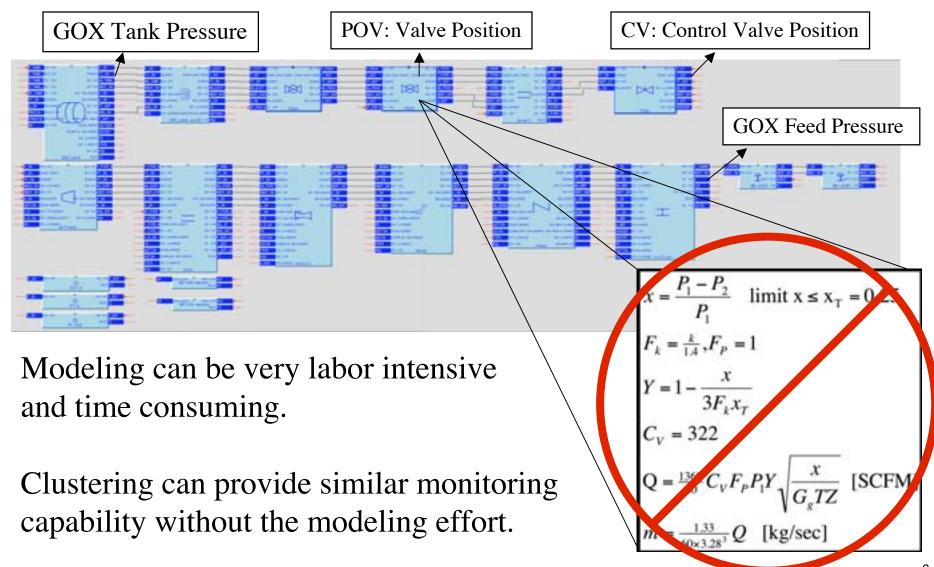






HCF Quantitative Model

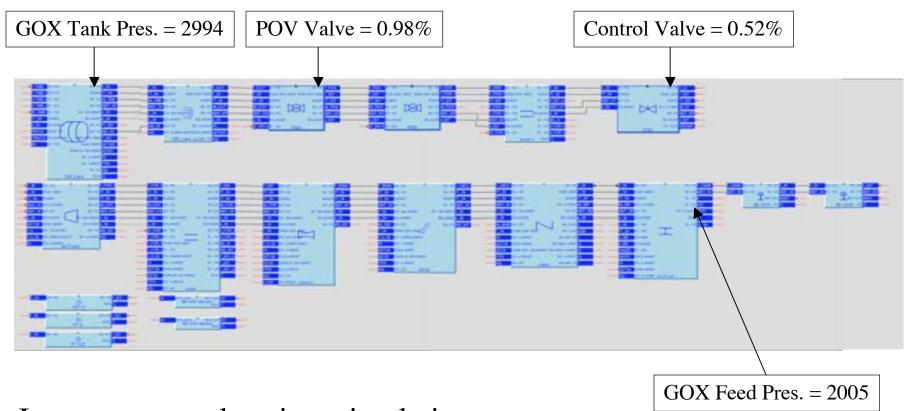






Model Based Monitoring





- Insert sensor values into simulation
- Run simulation
- Check for consistency between simulation and actual sensor readings

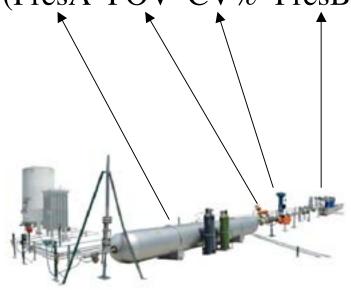
7



IMS Nominal Data Vectors



(PresA POV CV% PresB delta_PresA delta_PresB)



- Nominal sensor data is used to establish general relationships between parameters
- Training data can be collected from the system and from simulations
- Time dependencies modeled using differential parameters or by grouping consecutive data frames into a single vector

Inductive learning techniques are used to develop classes of nominal data vectors for different operating regimes. These classes allow the monitoring system to identify nominal data frames even if they don't precisely match previously processed training data.

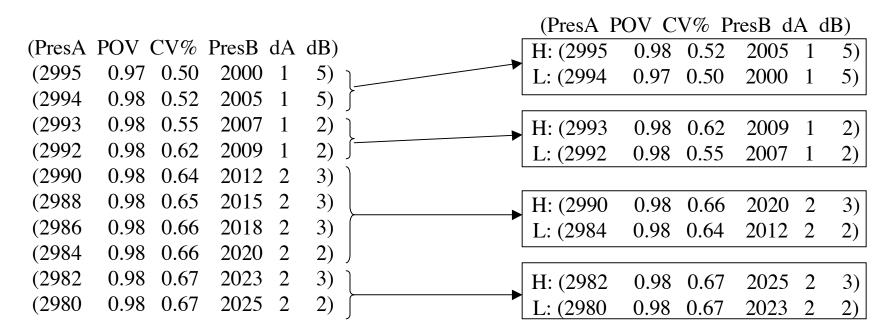


IMS Clustering Concept



Nominal data points are grouped into clusters of nearby points that specify acceptable ranges for parameters in a vector.





Archived Nominal Data Points

Generated Nominal Clusters



IMS Clustering Technique



For Each Training Vector*:



1. Find the closest cluster in the database.

$$(2992 \quad 0.98 \quad 0.62 \quad 2009 \quad 1 \quad 2)$$

2. Compare distance between the vector and cluster to threshold value.

Distance(V,C)
$$\leftarrow$$
 2 ?

3. If distance is within the threshold, expand cluster to include the vector. Otherwise, create a new cluster containing the vector.

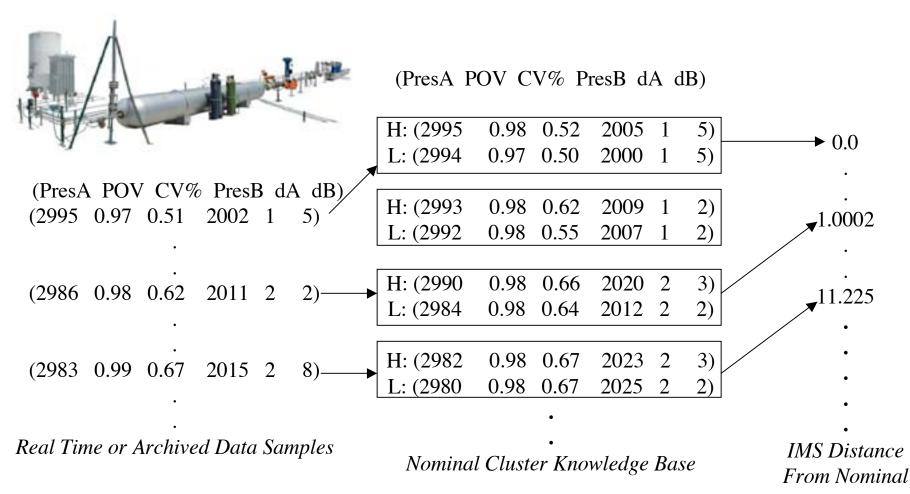
^{*} Vector values may be scaled or normalized as appropriate



IMS Monitoring Concept



For Each Input Vector: Find the closest nominal cluster in the database and report the distance of the vector from that cluster.





Some Prior & Current IMS Applications





Hybrid Combustion Facility Fuel Flow Monitoring

UH-60 Helicopter Engine Monitoring





ISS Beta Gimbal Unit and Control Moment Gyros

Stratospheric Observatory for Infrared Astronomy (SOFIA) telescope systems (simulation)





Aircraft Flight Control Surface Failure Situational Awareness (simulation)

ARC/JPL/DFRC F/A-18 System Monitoring Demonstration Flight (engine systems)





Shuttle Columbia **Ascent Analysis**



Shuttle Wing Leading Edge Impact Detection System (WLEIDS) and Space Shuttle Main Engine



Columbia Data Analysis



- There was enough (hidden) information in the STS-107 ascent telemetry data to indicate an anomaly ...
- The IMS method can help identify subtle but meaningful changes.

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STS-107 Ascent - IMS Analysis



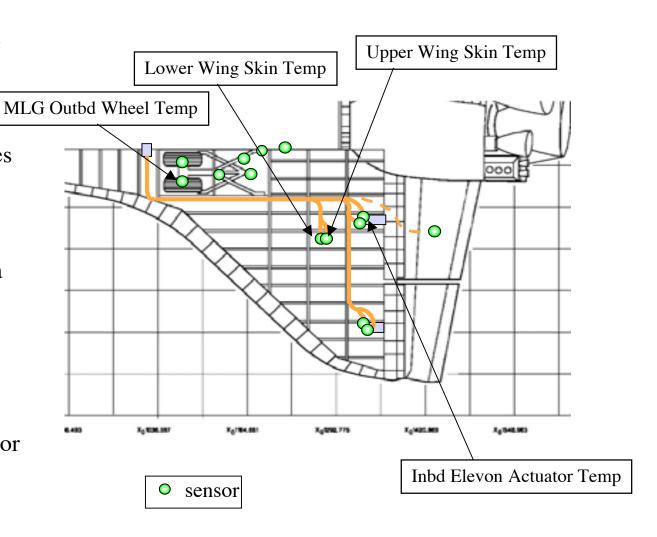
• Data vectors formed from 4 temperature sensors inside the wing

 Data covered first 8 minutes of each flight (Launch to Main Engine Cut Off)

 Trained on telemetered data from 10 previous Columbia flights

Normalization:

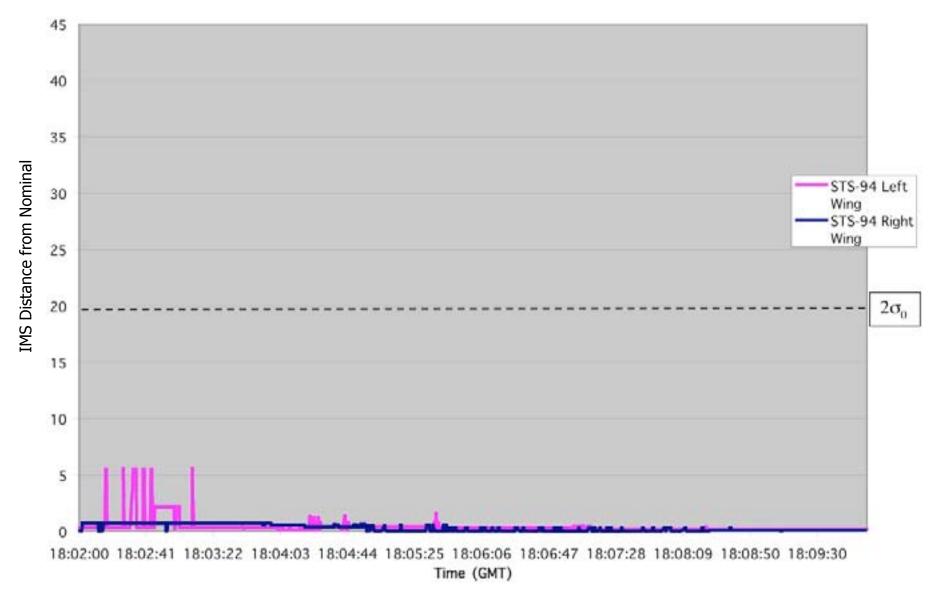
• Data expressed as value relative to a reference sensor





STS-94 Launch IMS Analysis

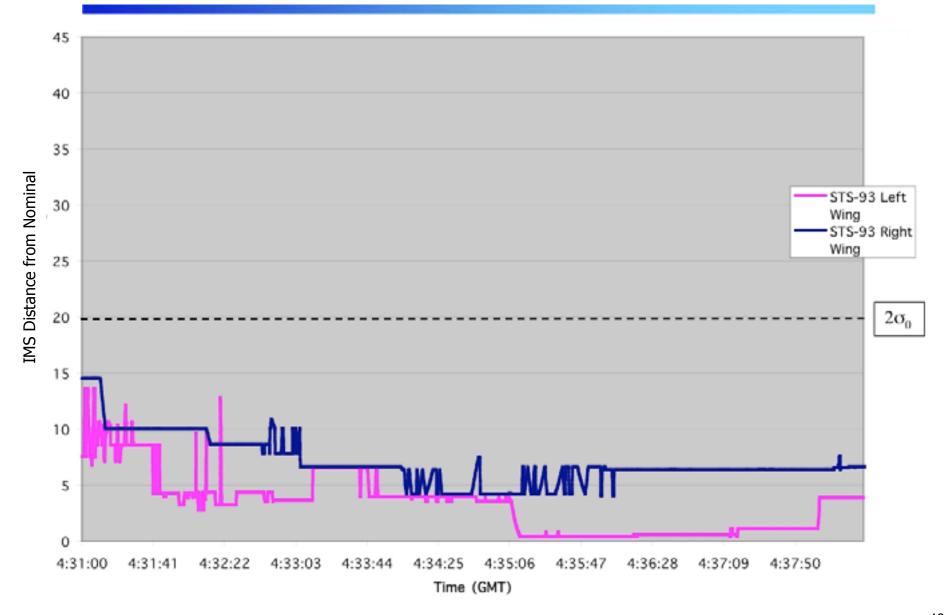






STS-93 Launch IMS Analysis

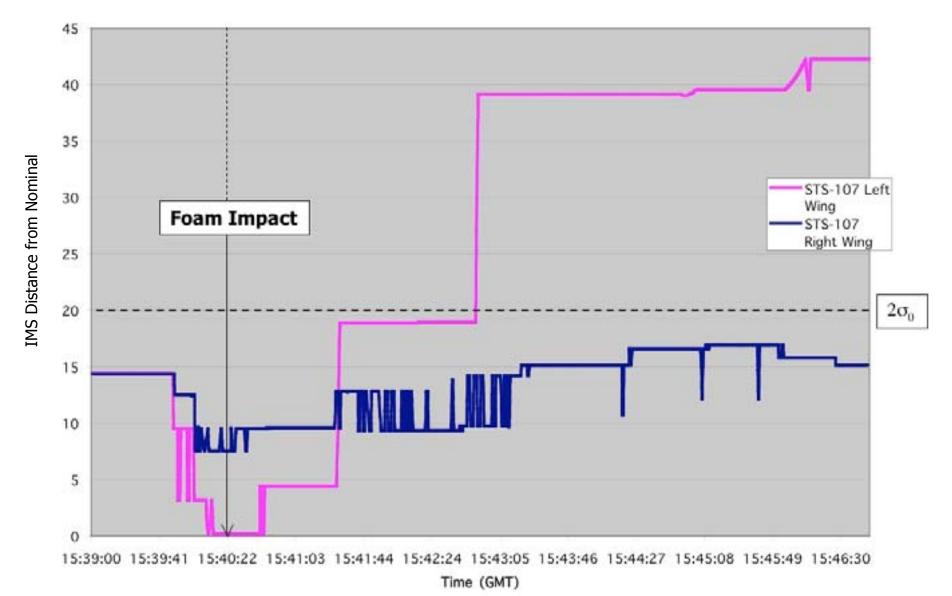






STS-107 Launch IMS Analysis







STS-107 Conclusions



- There were subtle deviations from nominal in left wing telemetry data subsequent to foam impact.
- The differences were "amplified" when data from multiple sensors were correlated with each other using IMS.
- Right wing telemetry remained nominal through ascent.
- IMS could be a valuable tool for on-line or off-line analysis of telemetry data for identification of subtle changes from past averages.



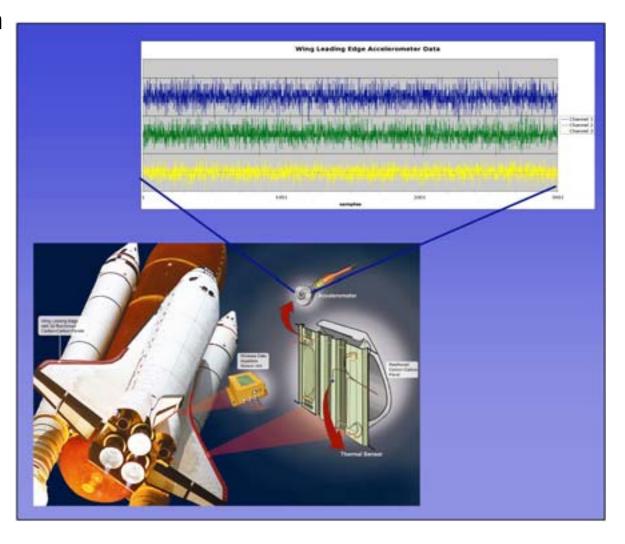
Space Shuttle Orbiter Wing Leading Edge Impact Detection System



IMS analysis of normalized WLEIDS data collected from the STS-114 mission has produced characterizations of patterns expected during quiescence and periods of known vehicle activity.

Downlinked data samples from future missions can be compared to these patterns for correlation to expected nominal conditions.

IMS identified deviations from expected nominal conditions may indicate possible impact events and prompt further investigation.

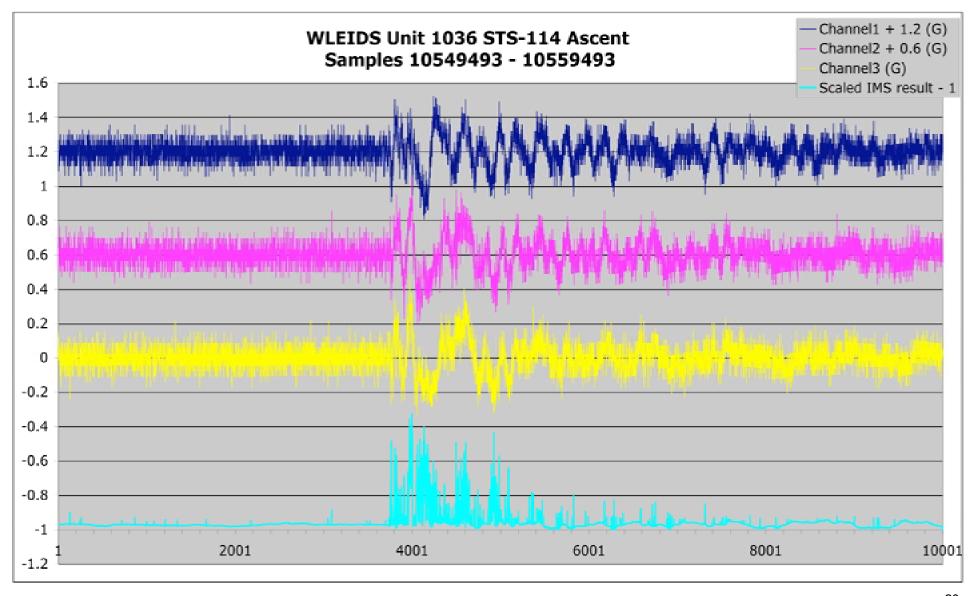


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IMS WLEIDS response to LO₂ and LH₂ feedline disconnects vs. background signal







F/A-18 ISHM Technology Demonstration





A joint effort between DFRC, ARC, and JPL to:

Assess the feasibility of using high-performance aircraft as a low-cost flight experiment platform for ISHM software proposed for space flight

Further mature and validate monitoring technologies developed by JPL and ARC through integration in flight-qualified hardware and by flight experimentation



F/A-18 Installation





RTD Intelligent Data Acq. Node

Processor: 300 MHz Geode 686

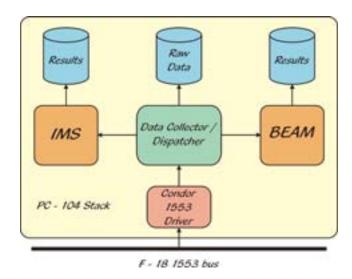
Storage: Flash Memory Disk

O/S: Linux

Data Bus: 1553A

Data Rate: 20 Hz





Software Architecture



Hardware Installation

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F/A-18 Hardware in the Loop Simulator



23





Initial development, integration, and testing was performed on the DFRC real time F/A-18 simulator with integrated hardware systems.



F/A-18 Training Data and Parameters



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Training data: 5 flights of target aircraft (Tail # 852) ~8 hours of flight time

Parameters Monitored:

- Controls/Environment Static Pres., Angle of Attack, Mach No., Side Slip, Power Lever Angle, Ambient Temp., Normal Accel., Engine Inlet Temp., Nozzle Position, Fuel Inlet Temp.
- Engine Status Narrow Band Vibration, Broad Band Vibration, EGT, Compressor Discharge Pres., Turbine Discharge Pres., Low Pres. Rotor Speed, High Pres. Rotor Speed, Oil Pressure, Fuel Flow

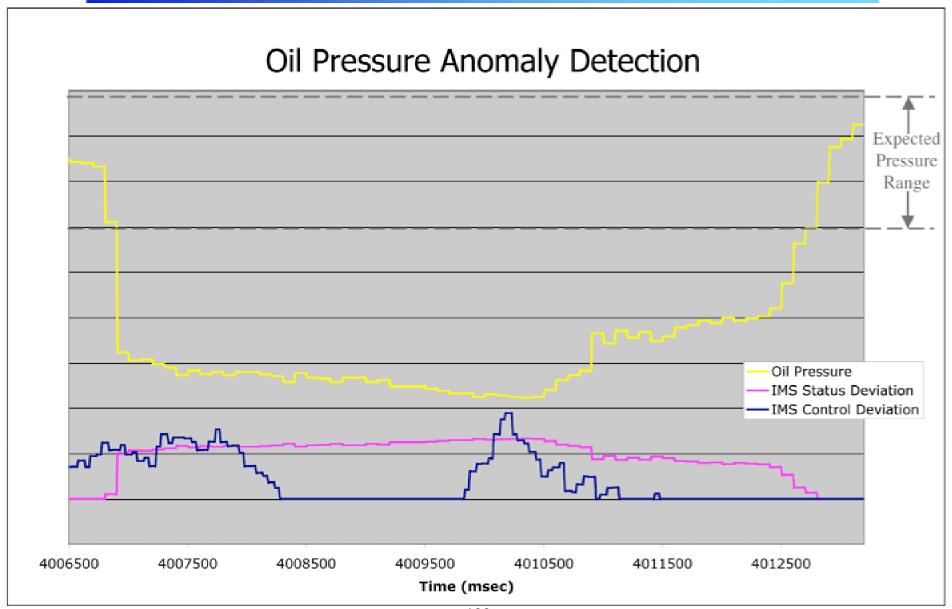
Successfully flew 25 test flights August - November 2005

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Some F/A-18 IMS Results







ISS Control Moment Gyros



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ISS Control Moment Gyros
On the Z1 Truss

The CMG operate as momentum storage devices that exchange momentum with the International Space Station (ISS), through induced gyroscopic torques.

CMGs were adopted as the non - propulsion effectors that would provide continuous attitude control yet would not violate the requirements of the micro-gravity environment.

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ISS CMG1 Failure & Analysis



"This morning, the ISS lost one of its four CMGs (control moment gyroscopes), located in the Z1 truss on top of the Node. After overnight briefly exhibiting some vibratory spikes, bearing temperature increase and motor current fluctuation, possibly also a small drop in wheel speed (from 6600 RPM), CMG1 at first returned to nominal operation, but failed during the morning hours, coming to a stop within 20 minutes."

- June 8, 2002 ISS On-Orbit Status Report

Currently performing IMS analysis of CMG data to assess feasibility of automated monitoring for this application

CMG1 Monitored Parameters:

Wheel Speed, Spin Motor Control Current, Electronics Assembly Current Inner Gimbal (IG) Angle, IG Angular Rate, IG Torquer Current Command Outer Gimbal (OG) Angle, OG Angular Rate, OG Torquer Current Command Requested Torque, Temperature 1, Temperature 2, Vibration

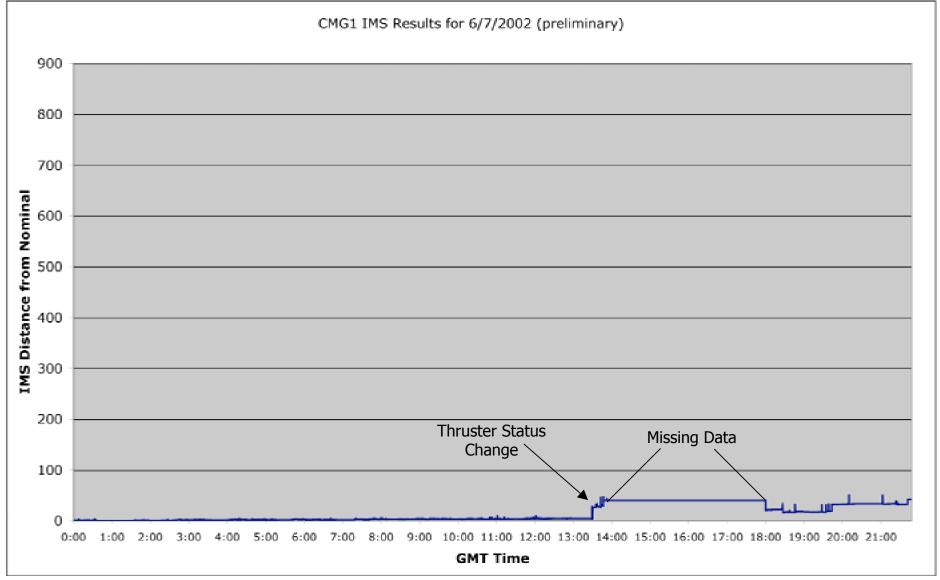
IMS trained on data collected on 6/5/02 - 6/6/02

27 191



Results One Day Prior to CMG1 Failure

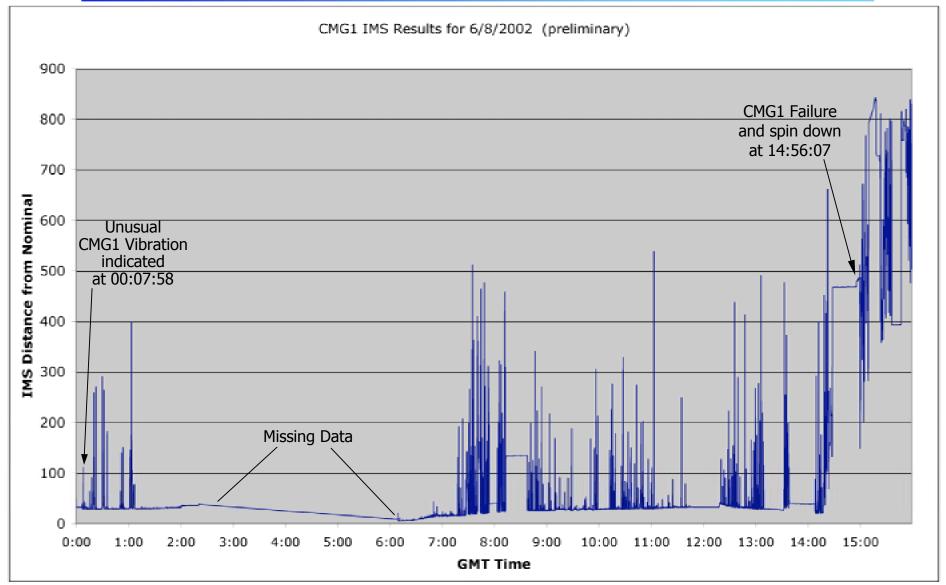






Results Day Of CMG1 Failure

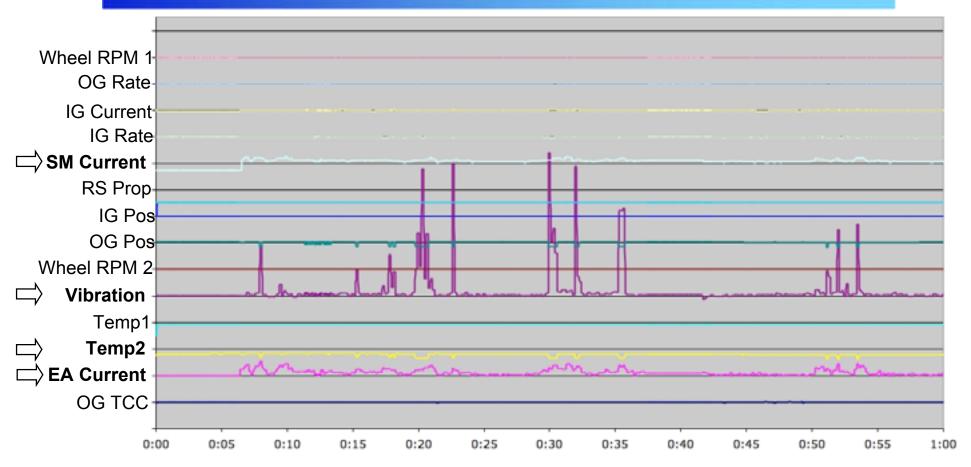






Individual Parameter Deviations





"briefly exhibiting some vibratory spikes, bearing temperature increase and motor current fluctuation"

The distance individual parameters fall from the closest match cluster can give some indication of the source of the anomaly



Some Features & Benefits



• Sensor Fusion

- Analyzes relationship between sets of parameters (complements commonly used individual parameter monitoring)

• Early Alert

- May detect possible problems before individual parameter limits are exceeded

• Historic Perspective

- Discovers and highlights differences between current and historic system behavior

• Real Time Monitoring

- In many cases the monitoring algorithm can support near real time processing of telemetry data

• Focused Analysis/Reconfiguration

- Rapid learning/retraining capability allows on the fly analysis of arbitrary sets of relevant parameters when investigating anomalies and/or rapid monitoring reconfiguration after a sensor or equipment failure



HotMiner: Discovering Hot Topics from Customer Support Logs

Malu Castellanos
Intelligent Enterprise Technologies Lab
Hewlett-Packard

Malu Castellanos is a senior researcher in the Information Services and Process Innovation Laboratory at Hewlett-Packard Laboratories in Palo Alto, CA, USA. Since 1998 she has been applying data and text mining techniques to develop intelligent solutions to different kinds of business-related problems and integrating these techniques in the development of a platform for business process intelligence. She received a B.S. in Computer Engineering at the National University of Mexico and a Ph.D. in Computer Science from the Polytechnic University of Catalunya in Barcelona. Prior to joining Hewlett-Packard, she spent six years as a professor at the Information Systems Department of the Informatics School at the Polytechnic University of Catalunya teaching databases and leading national and international research projects mostly related to database interoperability. She has more than 40 publications in international conferences, journals, and book chapters, and has participated in different roles in the organization of a number of international conferences and workshops. Her current interests are business process/operations intelligence, interoperability-related technologies, business intelligence, and data and text mining applications.

In a previous life she spent a year participating in the testing of the first Mexican satellite being built at Hughes Aircraft Co., and then in the final testing inside of the Space Shuttle Columbia at NASA.

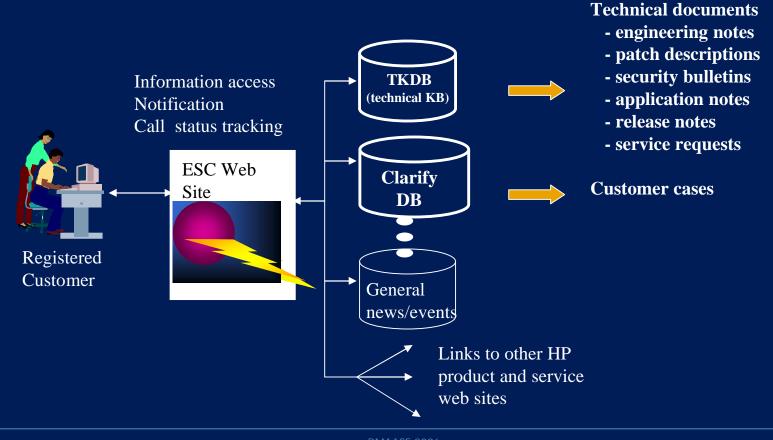


HotMiner: Discovering Hot Topics from Customer Support Logs

Malu Castellanos Hewlett-Packard Labs Palo Alto

HP Electronic Customer Support Center

Reduce HP support costs by providing customers with Web access to a suite of support services



Business Motivation

- Reduce costs of customer support \$\$\$\$
 - Turn call center customers into self-solving customers and reduce the reverse conversion
 - Make search easy!
 - Provide intuitive hierarchies of technical documents
 - Make hot topics readily available (80% rule)
 - Assist in the generation of certified documents
 - Only a small percentage of cases turn into RCENs

Technical Motivation: Challenges

How to obtain meaningful hot topics?

 How to categorize technical documents according to users perspective?

How to deal with dirty text?

The Golden Mine



- Customer support logs contain extremely valuable information!
 - all the information about the customers technical problems, information needs, interests
 - Self-solving customers
 - -CIDB (last 20 searches/customer)
 - Usage log (customer actions)
 - Web log (docs opened)

one logical search log

- Reporting customers
 - -Case log

Self-solving Customer Logs



CIDB (customer ID, 20 most recent search strings with datestamps)

```
CA10 102 1 1_0_0#MODEDESC~HPUX~SB:PA:EN:SR:MD~35~980504~0~+hp ux 11.0 white paper MODEDESC~HPUX~PA:EN:MD~13~980421~0~+y2k  
CA100277 102 1 1_0_0#MODEBOOL~HPUX~SB:PA:EN:SR:MD~6~980504~0~+swap priority  
MODEBOOL~HPUX~SB:PA:EN:SR:MD~849~980429~0~+"tape read error"  
MODEBOOL~HPUX~SB:PA:EN:SR:MD~860~980428~0~+HP-UX bug  
MODEBOOL~HPUX~SB:PA:EN:SR:MD~0~980427~0~+DLT7000 and 10.0
```

Usage log (IP address, timestamp, customer ID, action)

```
04/01/98, 06:45:20 | HTTP | CA199669 | usa | IP address....edu* | atq | reviewResultsDoc | 1/0.91/0.14 | 1 04/01/98, 06:45:20 | HTTP | CA24170 | japan | IP addres....co.jp | wpsl | displaypatch | 1/0.73/0.16 | PHNE_9380 | 1 04/01/98, 06:45:21 | HTTP | CA20937 | usa | IP address....com | atq | reviewResultsDoc | 1/0.89/0.14 | 1 04/01/98, 06:45:21 | HTTP | CA1482 | usa | IP address...com | atq | doSearch | 4/1.01/0.14 | 1 04/01/98, 06:45:30 | HTTP | unknown | unknown | IP address...103 | common | admit | 1/0.20/0.14 | 1
```

• Web log (IP address, timestamp, document retrieved)

```
208.194.35.60 - - [01/Mar/1998:05:54:30 -0800]

"GET/atq/bin/doc.pl/sid=06da17571d77589c4d/screen=atqDocTextSrch/?PRONTOID=157344 H5

208.194.35.60 - - [01/Mar/1998:05:55:53 -0800] "GET

/atq/bin/doc.pl/sid=52f8871412574d6ca7/screen=atqDocTextSrch/?PRONTOID=147002 H8

crawl4.atext.com - - [01/Mar/1998:00:32:11 -0800] "GET

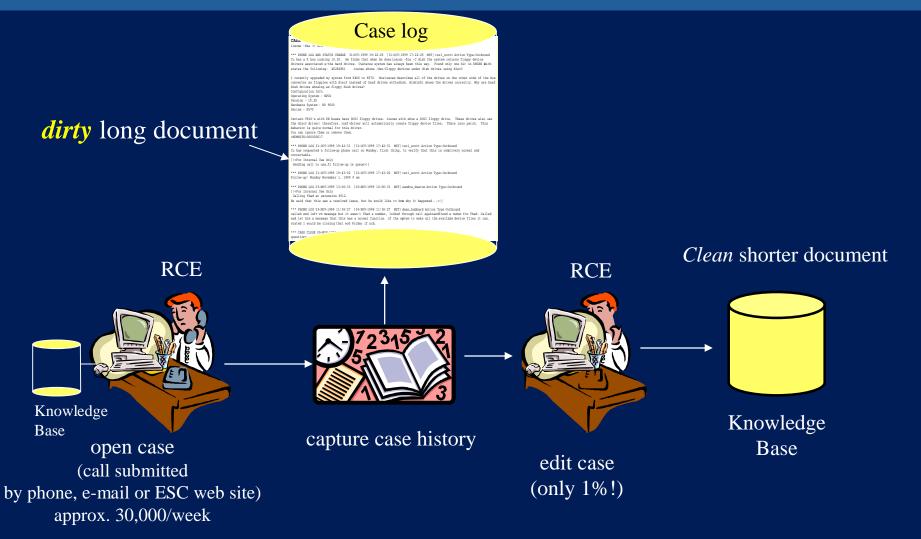
/common/bin/doc.pl/sid=ce444314027f450144/screen=commonWhatsNew/ HTTP/1.0"
```

Need to be correlated

^{*} IP addresses have been removed due to privacy issues

Reporting Customer Logs





Cases are dirty!

stated I would be closing thei edd Friday if ncb.

questions on divices automatically created

*** CASE CLOSE 05-Nov-1999 13:15:06 [05-NOV-1999 13:15:06 MST] Jim Anderson

specific terminology

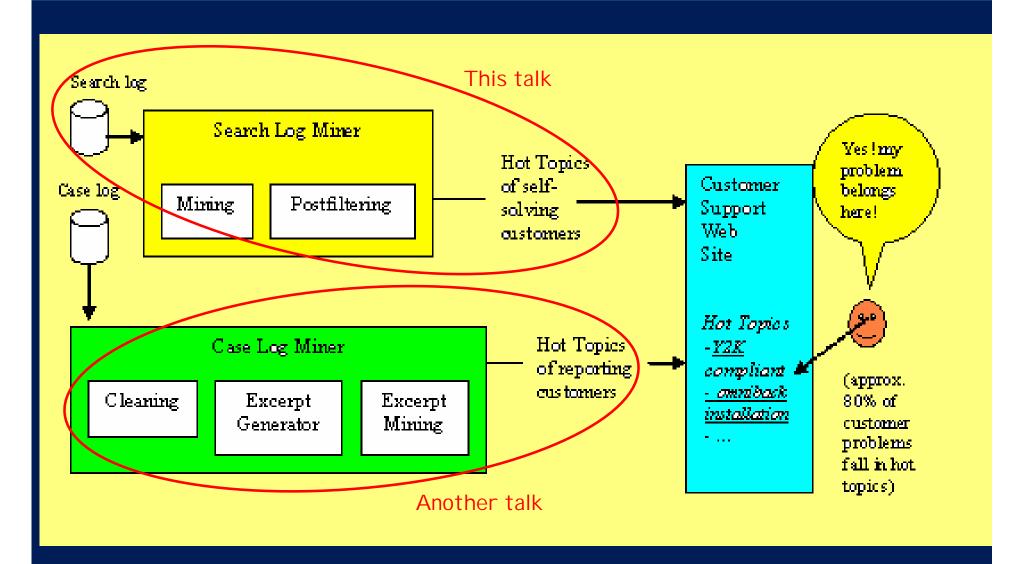
abbrev

```
abbrev+glued
CASE EXAMPLE:
                         *** PHONE LOG 31-OCT-1999 19:06:43 [31-QCT 1999 17:06:15 MJ] COLLI DMICH
ioscan -fna -C disk showing floppy device drivers associated w/the hard drives
                                                                                 missing punct. mark
*** PHONE LOG AND STATUS CHANGE 31-OCT-1999 19:22:25 [31-OCT-1999 17:22:25 MST
℃u has a K box running 10.20. He finds that when he does ioscan -fna -C disk the system returns floppy device
drivers associated w/the hard drives. Custates system has always been this way. Found only one hit/in KMINE which
states the followi
                                     scan shows /dev/floppy devices under disk drives using disc3 🖊
                  glued words
I recently upgraded my system from K460 to K570. pow ioscan describes all of the drives on the other side of the bus
converter as floppies with disc3 instead of hard drives with sdisk. diskinfo shows the drives correctly. Why are hard
disk drives showing as floppy disk drives?
Configuration Info
                                    missing upper case
Operating System - HPUX
Version - 10.20
Hardware System - HP 9000
                                                                misspelling is valid word
Series - K570
Certain T500's with PB buses have SCSI floppy drives. ioscan with show a SCSI floppy drive. These drives also use
the disc 3 driver; therefore, insf/driver will automatically create flopy device files. There is no patch. This
behavior is quite normal for this driver.
You can ignore them or remove them.
                                            misspelling is invalid word
<NUMHITS=000000017
* * PHONE LOG 31-OCT-1999/19:42:31 [31-OCT/1999 17:42:31 MST] John Smith Action Type:Outbound
Cu has requested a follow-up phone call on Monday, first thing, to verify that this is relatively normal and
correctable.
[!<For Internal Use Only
 Sending call to use fl follow-up le queue>!]
*** PHONE LOG 31 CCT-1999 19:43:02 / 31-OCT-1999 17:43:02 MST] John Smith Action Type:Outbound
Follow-up Monday November 1, 1999 9 am
*** PHONE Log 03-NOV 1999 13:06:33 [03-NOV-1999 10:06:33 MST] Mary Jones Action Type; Outbound
[!<For Internal Use Only
 Calling Ted at extension 1234.
He said that this was a resolved issue, but he would like to know why it happened...>!]
*** PHONE LOG 03-NOV-1999 11:36:27 [03-NOV-1999 11:36:27 MST] Jim Anderson Action Type:Outbrund
called and left vm message but it wasn't Ted s number, looked through call again andfound a nuber for Ted. Called and
let him a message that this was a normal function of the system to make all the availabe device files it can.
```

```
Database backups are done nightly.
                                                                           Bad grammar
Customer go to the ftp site and puts pos.txt there.
I retrieve it.
Here's hte message again,
bad id in file pos.txt, line #1, field #2.
                                                                               Syntactic errors
Here the first few lines from pos.txt
                                                             File dumps
There is nothing syntactically wrong with line 1. The problem must be with a database reference. We could get into
a tangled web trying to fix this.
I suggest readascii on just the MMDB so customer can do backups. Customer can recover the database later.
Customer already ran -readascii -mmdb /.....
Devices & Media
[12:1012]cannot access the file
This refers to an OmniBack configuration file.
On the Cell Manager, "i70-1.mcn.lucascargo.com"
                                                                commands
```

HotMiner Architecture





Part I: Mining Search Logs

Use of two different views of a document

Query view

- the collection of queries used to open a document provides a query view of the document in terms of user keywords.
- Used to discover hot topics from the customer perspective

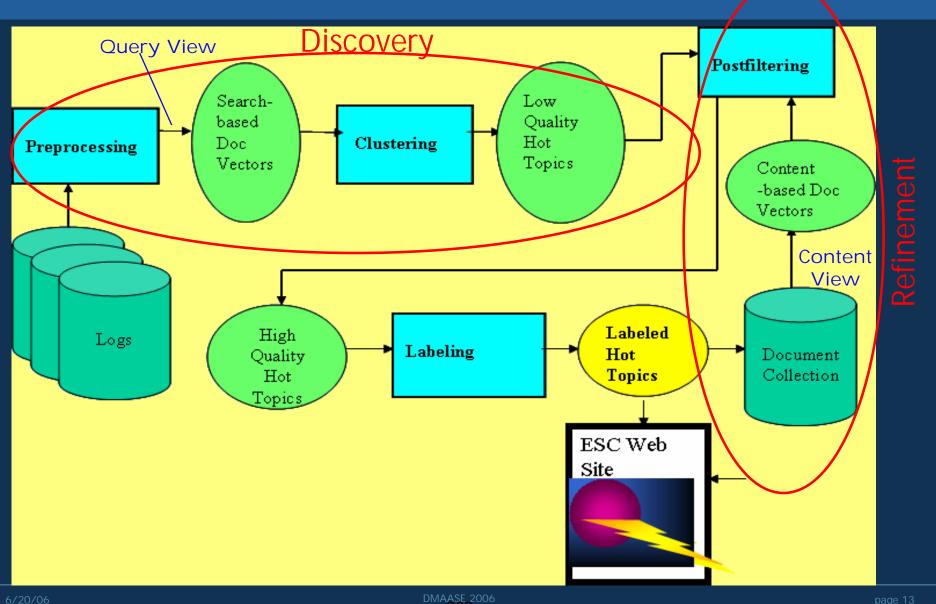
Content view

- The collection of words in the content of a document (typical view).
- Used to improve the precision of hot topics

Mining Search Logs: Stages

- Two main stages
 - Discovery of hot topics from query view
 - Preprocessing
 - Clustering
 - Refinement of hot topics from content view
 - Post-filtering
 - Labeling

Search Log Miner Architecture



Step 1: Preprocessing

- Data extraction from logs
- Cleaning
- Correlations (3-way joins)
- Computing statistics (hot keys, hot docs, etc)
- Derive query view of hot docs
- Transform query views into vectors

Correlation: some Data Issues

- Date but no time in CIDB entries
 - Sequence within a day is lost when search strings are extracted
 - Add sequence numbers to preserve the order
- Timestamp skewness
 - web log TS lagging behind usage log TS

```
- Web log:

IP address1* - - [02/Apr/1998:13:28:15 -0800] "GET
/atq/bin/doc.pl /sid=4626d1531c4c7210e8 /screen=atqDocTextSrch
/?PRONTOID=150351 HTTP/1.0" 200 5472

- USage log:

04/02/98, 13:28:14 | HTTP | CA228104 | usa | IP address1* | atq | reviewResultsDoc |
```

* IP address removed for privacy issues

Preprocessing: Correlations (example)

- 1. Identify some hot document: prontoid=150351 (from web log)
- 2. Find web log entries which retrieved the document

```
IP_address1.com - - [14/Apr/1998:08:42:39 -0700] "GET
atq/bin/doc.pl/sid=39d3112009ce14d5b4 /screen=atqDocTextSrch/?PRONTOID=150351
HTTP/1.0" 200 5470
```

3. Find search actions on that day preceeding the retrieval of the doc by correlating with usage log via IP address and timestamp to get Customer ID and compute corresponding sequence number

```
04/14/98, 08:35:01 | HTTP | CA1208 | usa | IP_address1.com | atq | doSearch | 23/1.20/0.22 | 1

04/14/98, 08:41:46 | HTTP | CA1208 | usa | IP_address1.com | atq | doSearch | 8/1.01/0.25 | 1
```

4. Find the search string the customer issued before opening the doc by correlating with CIDB via customer ID, date stamp and sequence

```
CA1208 102 1 1_0_0 ... MODEDESC~HPUX~SB:PA:EN:MD~6~980414~0~+KNC041497001

MODEBOOL~HPUX~EN:MD~56~980414~0~+2000 AND patches • •
```

Preprocessing: Document Vectors

Query views (after correlating logs):

Docume	Query Strings				
15321	Y2k; 2000 compatibility; year 2K ready;				
539510	Omniback backup; recovery; OB;				
964974	sendmail host is unknown; sender domain sendmail; mail debug; sendmail; mail; mail aliases;				

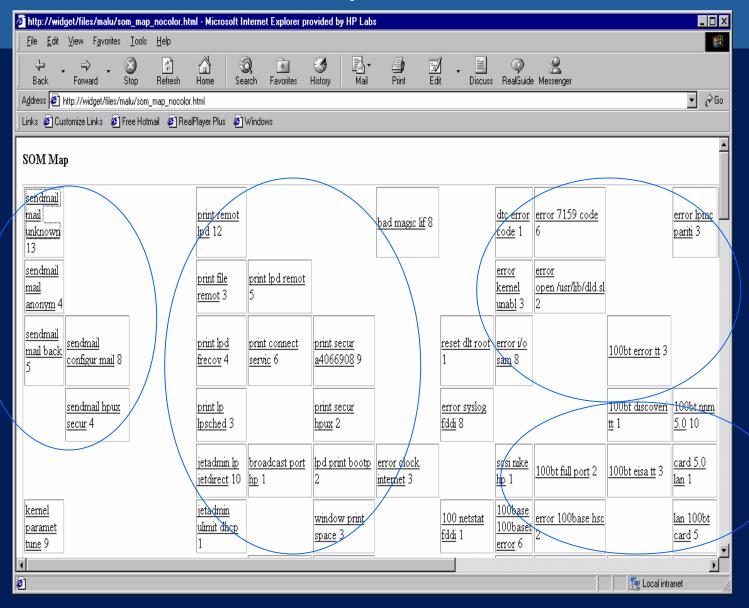
Query view numerical vector:

sendmail	mail	sender	domain	aliases	host	unknown	debug
0.25	0.16	0.08	0.08	0.08	0.08	0.08	0.08

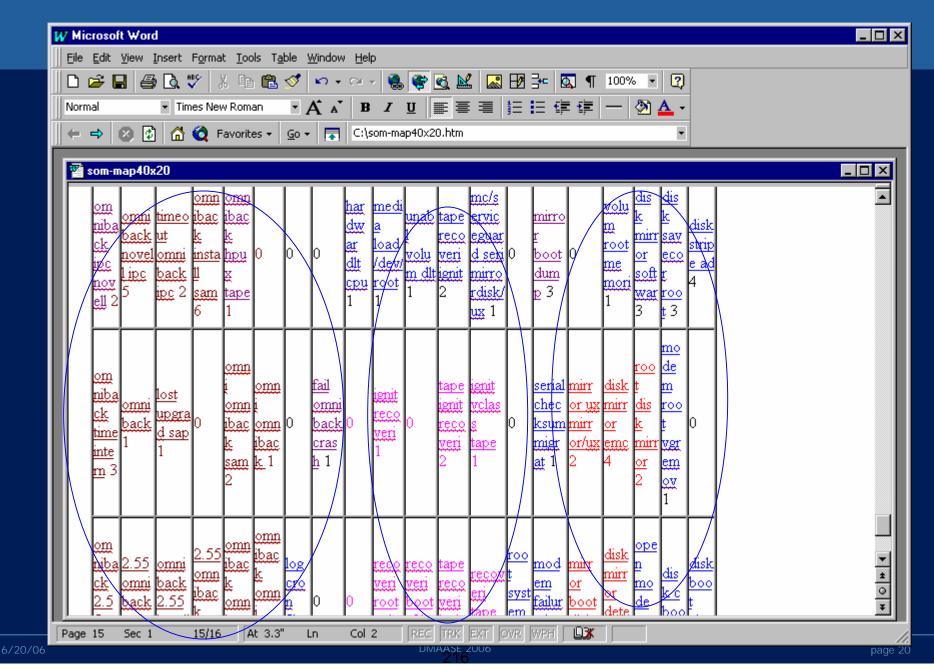
Step 2. Clustering

- Objective: group hot docs wrt the hot keys used in the queries after which the docs were opened.
- The relationships between a group of hot keys and a group of hot docs constitutes an abstraction of a hot topic.
- The method is independent of the clustering algorithm used
 - We used SOM_PAK implementation of Kohonen's SOM algorithm
 - Output allows for easy implementation of the visualization of the map -> facilitates our analysis of the evolution of topics

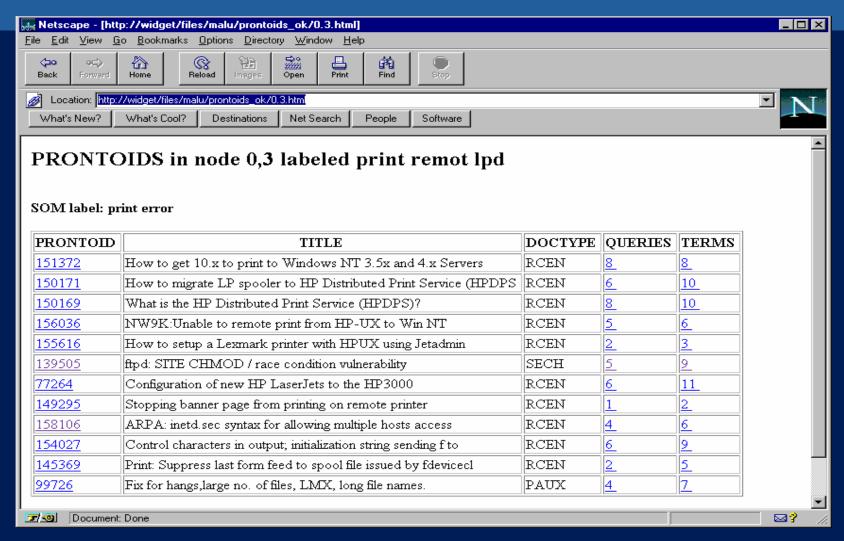
Visualization of SOM map



Visualization of SOM map



Documents in Hot Topic "Print"



Hot topics clusters match the users perspective

Step 3. Postfiltering

- Uses the content view of the documents
 - Substeps
 - Preprocessing
 - Cleaning
 - stop words
 - stemming
 - normalization
 - Document transformation into vectors
 - feature selection
 - vector computation (weights)
 - Similarity computation
 - Topic elimination
 - Document elimination

Postfiltering: Vector Representation

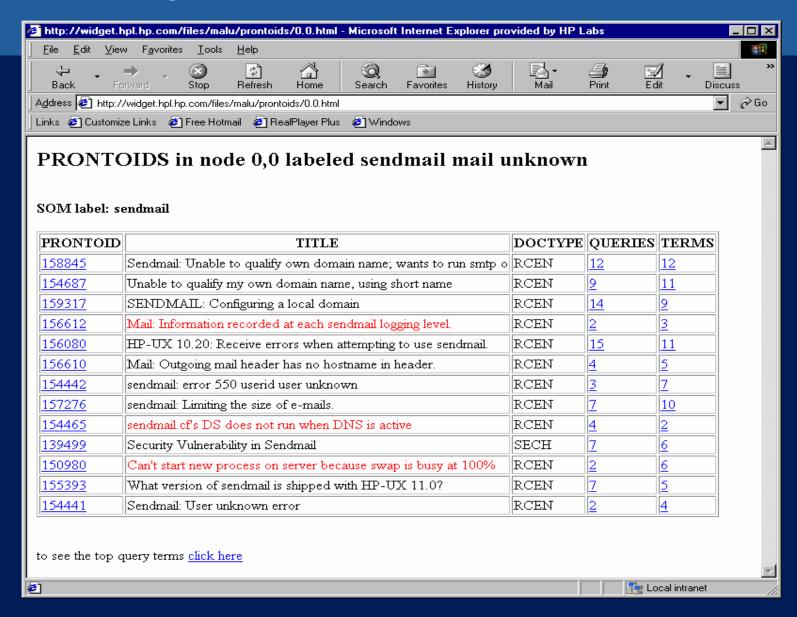
- document contents represented by numerical vectors
- feature selection
 - which terms to use to represent the doc as a vector
 - several alternatives were experimented:
 - 1. query words that characterize a cluster
 - 2. terms in the titles of the documents in a cluster
 - 3. all terms in the contents of the documents in a cluster
 - 4. the first 50 terms in the contents of the docs in a cluster
- weighting
 - modifies term frequency by combining alternatives 2 and 3: weight_{termij} = K (freq term_{ij} / |doc_j terms|)

where K > 1 if term belongs to titles_{clusterdocj}

Postfiltering: Similarity Computation

- Cosine coefficient used to compute similarities
 - At document level
 - At cluster level
 - Coefficient of dispersion
- Cluster elimination
 - Identify very bad clusters
- Document elimination
 - Identify extraneous documents
- Statistical approach to determine threshold

Postfiltering: extranous docs is valuable info



Part II: Mining Case Logs

- The majority of customers still open cases
- Hot topics are incomplete without considering cases
- But cases are dirty!
 - The majority of text mining techniques assume clean text
 - Added challenge
 - Cleaning
 - Summarization (excerpts)

preprocessing tasks

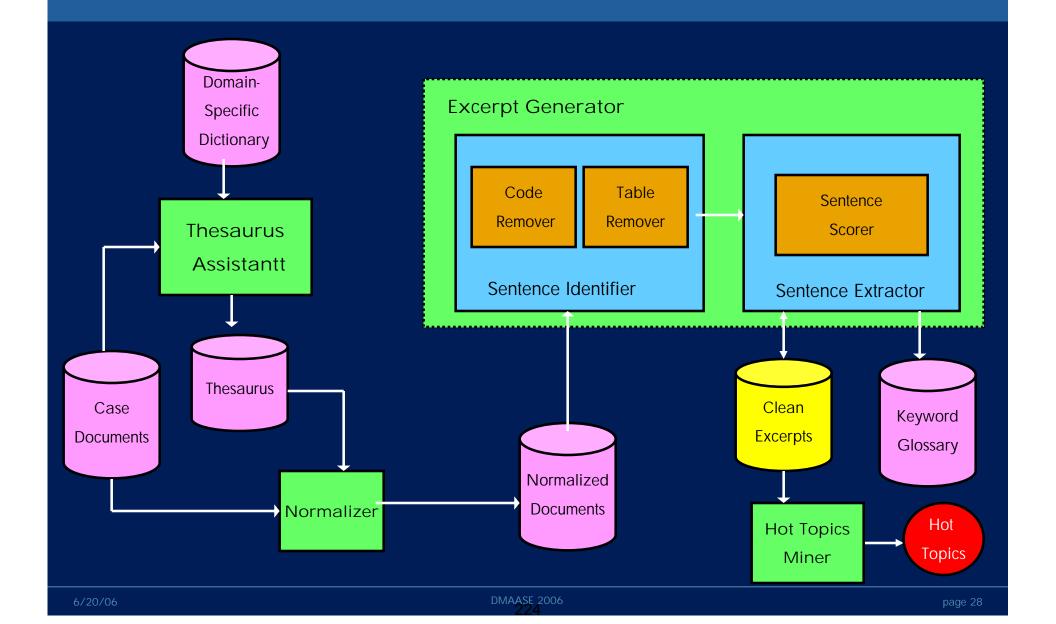
Preprocessing modules

	Problem	Effect	Functionality Required	Tools**
Stage 1	Typos Misspellings Abbreviations	False word occurrences	Unify representation of words	ThesaurusAssistantNormalizer
Stage 2	Code Dumps Cryptic tables	Complicate sentence identification possibly w/o adding value	Removal* of code, dumps and tables	CodeRemoverTableRemover
Stage 3	Too much irrelevant content	Irrelevant content introduces noise for hot topics identification	Obtain excerpts	SentenceIdentifierSentenceScorer

^{*}Removal only for sentence identification, not necessarily for summarization

^{**}Tools in the toolkit can be mixed and matched for different applications

Case Log Miner Architecture (topic of another talk)



Conclusion

- Lots of experiments done with real data
- Found useful empirically: discovered new (and some surprising) hot topics
- Difficulty in full validation of the approach (lack of domain expert)
- Approach applicable to other domains



We've got data – Now what to do with it?

Walter Thomas III NASA Goddard Space Flight Center/NESC

Abstract: The author discusses experiences with researching databases to derive data providing reliability assessments and trending for spacecraft and civil aircraft. Two valuable and widely applicable analysis tools, Weibull and Crow-AMSAA analyses, are briefly described. Several analysis examples from space, civil aircraft, and other applications are presented.

Walter Thomas had 16 years experience in the technical glass and electronic component and packaging industries before joining NASA. He has consulted for component suppliers and aerospace manufacturers. At the Goddard Space Flight Center he has worked in the areas of electronic parts, components and packaging, and reliability engineering. He has performed and managed reliability tasks and provided risk assessments for part, component, and systems issues affecting space flight and other programs. His areas of expertise include Weibull and other statistical analyses, field performance evaluations, system modeling, and technical and electronic glass applications. He presently works as a Reliability Engineer in the Systems Safety and Reliability Office. Mr. Thomas holds a B. Ceramic Engineering from the Georgia Institute of Technology and a M.S., Ceramic Engineering, from the University of Illinois.

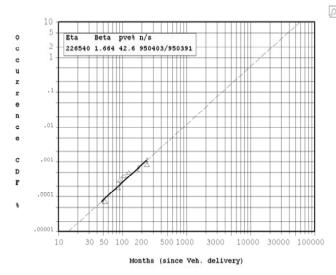
We've got data - Now what to do with it?

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NASA GSFC/NESC

- Usually, we want to extract information about a physical characteristic or probability to estimate a risk or occurrence "rate."
- The data must "fit" the characteristic or probability desired: occurrence frequency, failure rate (CFR), are failures affected by lifetime?, etc.
 - > i.e., KNOW YOUR DATA, understand underlying statistics.
- For "life data analyses," two valuable tools are Weibull and Crow-AMSAA (CA) analyses.

Why Weibull?

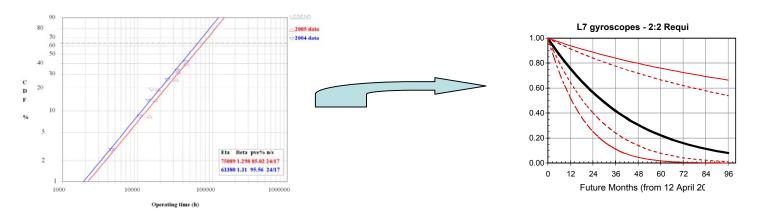
- Provides reasonably accurate failure analyses and forecasts
 with extremely small samples good results with ~10-15 failures,
 excellent with 20-30, even can make predictions with only 2 or 3.
- Simple and useful graphical plot:



- log (time, cycles, mileage) [x-axis] vs. cumulative failure probability [y-axis]
- linear fit to failure points indicates goodness of fit
- slope parameter (β) shows failure character vs. lifetime; indicates failure mode physics
- "characteristic life" (η) is the "time to failure" parameter for Weibull distribution (not MTBF/MTTF unless b ~ 1!)
- Weibull normally is "one failure mode at a time."

Why Weibull? (cont'd)

- In the space/aircraft businesses, we usually are dealing with a few failures among tens to thousands of non-failed units.
- Weibull distribution emphasizes failures in the "lower left corner"
 - this is area we're interested as first ("lower left") failures are what will cause system problems/failures.
- Once a Weibull distribution is fit to failure data and a good (statistical) fit exists, future performance can be predicted (past performance is best indicator of future):



What is Crow-AMSAA (CA)?

(abstracted from Ref [1])

- Best available tool for tracking/trending events and forecasting: for example -
 - ✓ Tracking fleet/in-service performance
 - ✓ Trending safety and reliability events
 - ✓ Maintainability tracking/trending
 - ✓ Tracking management parameters & forecasting future levels

• Benefits [Ref. 1]:

- o Trend charts make reliability or safety more *visible and manageable*.
- o Reliability/safety program progress and change/improvement effects measured and displayed.
- o Predictions available *early* to compare against goals, allowing corrective action implementation.
- o Adverse (and beneficial) trends indicated *much sooner* and *more accurately* than moving averages.
- o System trends measured even with mixtures of failure modes.
- o Trend charts will verify engineering predictions of "fix" effectiveness for observed problems.
- Event growth analysed with intervals of missing or suspect data; provides good risk predictions even with these data deficiencies.
- Many corporations now believe CA is even more valuable than Weibull.

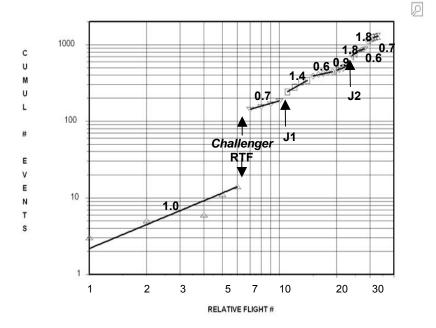
What is Crow-AMSAA? (cont'd)

- Originally tracked reliability growth in development processes to determine when motors/generators were good enough to put into production. (J. Duane GE, 1964)
- Original model derived empirically. Dr. L. Crow (Army Material Systems Analysis Activity AMSAA) developed statistical basis to model growth process and provide goodness-of-fit of data. Renamed *Crow-AMSAA* (*CA*) model by *IEC*.
- Aerospace Industries Association Technical Management Committee studied ('70s) array of growth methods applied to mechanical components concluded *CA was best*. U. S. Air Force study (1984) also concluded *CA best*, this involving both *electronic and mechanical* controls.
- The Statistics of CA CA is a "cousin" to the Weibull distribution:
 - o Both handle increasing, decreasing, and constant failure (event) rates.
 - o Interpretation of slope parameter is same for both.
 - o CA uses cumulative time scale (Weibull uses individual failure times).
 - o CA handles mixtures of failure modes (Weibull only one at a time).
 - o CA models the process, in which reliability (event rate) can change with time (Weibull cannot do this).
 - o Fulton Findings software (WinSmith VisualTM) provides statistical goodness of fit indicator, rate plots.

What is Crow-AMSAA? (cont'd)

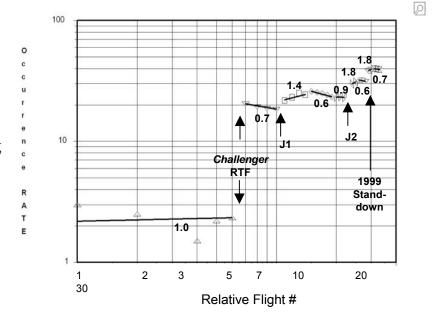
• CA 101:

- o Plot data (events) on cumulative occurrences vs. cumulative time chart.
- Look for data with linear trend; indicates a "stable" process (one that can be described by a CA model).
- o There may be jumps, or cusps, in the data this indicates some significant change having occurred in the process. (*This is a part of the analysis!*)
- For "stable" events slope indicates increasing, decreasing or static (unchanging) occurrence rates.
- o For "stable" process, one can predict future occurrences at future times. (Accurate to $\sim +/-10\%$.)
- o Any "jump," cusp, or slope change indicates something has changed in the process.



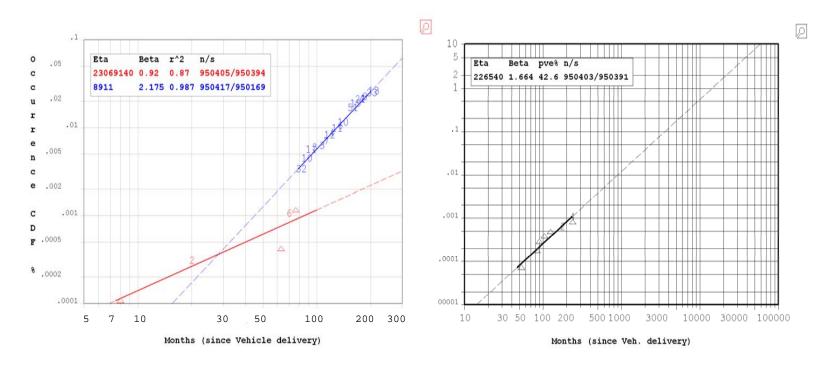
What is Crow-AMSAA? (cont'd)

- CA 101 (cont'd):
- The actual CA plot may not be clear to nonpractitioners. An "occurrence rate" plot (derived from the CA plot) is good for management tracking/presentations:
- ➤ Flat (no) slope (~ 1) means things are NOT changing
- ➤ Increasing slope (line trending *UP*; slope >1) = more events per time = things getting "worse."
- ➤ Decreasing slope (line trending *DOWN*; slope <1) = fewer events per time = things getting "better."
 - ❖ The later (decreasing slope) is what we are striving for!!



^[1] Robert B. Abernethy, The New Weibull Handbook, Fourth Ed., 2000-2003 - best reference for Weibull & CA.

^[2] See also www.barringer1.com, an excellent website for reliability tools; "Problems of the Month" has several examples using CA.

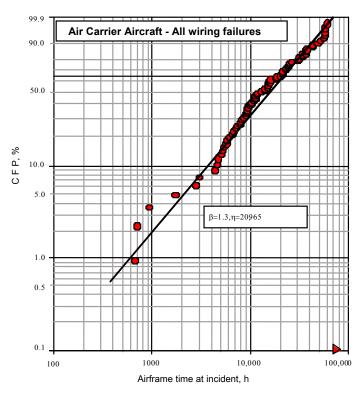


Wiring exposed conductors in OV103

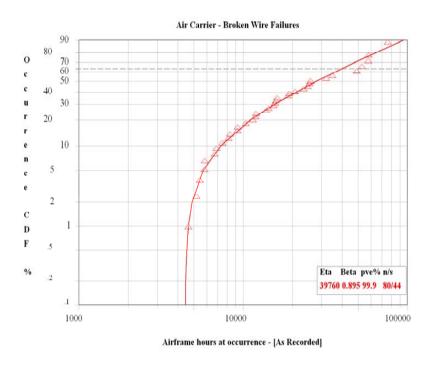
Infant mortality events for first 76 mos., then early wear-outs. Wiring, *if replaced*, would *not* show increased rate for ~ 6 y. Weibull results entered into NESC RJD FT model.

Wiring short circuits in STS OV103

Data indicate "early wear-outs." Results entered into NESC STS RJD fault tree model.

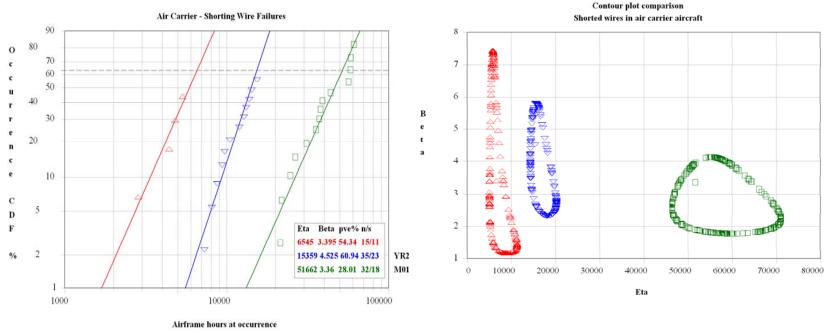


All incidents plotted; includes broken, chafed, loose, shorted wires. *Mixed failure modes!*



Broken wires (*ONLY*) plotted; excellent fit to Weibull three parameter; indicates ~4500h failure-free time before broken wires manifest -randomly occurring failures.

Civil Air Carrier Aircraft Wiring Incidents



Shorted Wires (*ONLY*) plotted, after separating apparent subpopulations

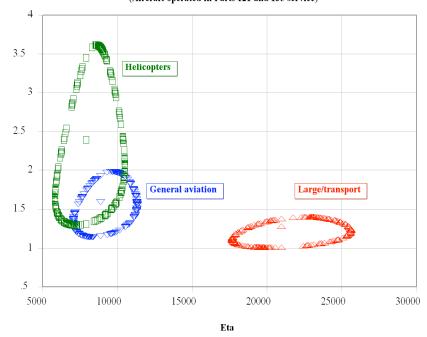
Contour plots of Shorted Wires data. Weibull slopes are equivalent (overlap on y-axis), therefore same mechanism indicated. (@ 90% confidence)

Civil Air Carrier Aircraft Wiring Incidents

Table II. Wiring failure data for comparing aircraft "classes."

Aircraft class	n	β	η, hours	Pve, %
Helicopters	8	2.4	7,900	86
General aviation	25	1.6	8,700	63
Large/transport	81	1.3	21,000	42

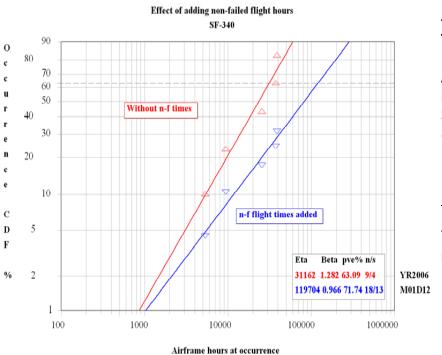
Weibull data comparing all wiring failures between helicopters, general aviation (GA), and transport category aircraft used in air carrier/air taxi/commuter service. Comparison of wire failures between aircraft classes (Aircraft operated in Parts 121 and 135 service)



Contour plots comparing all wiring failures among three aircraft categories. Slopes are equivalent, indicating similar failure behaviors.

Large transport failures occurred much later than helicopters and GA, which fail at equivalent times.

Civil Air Carrier Aircraft Wiring Incidents



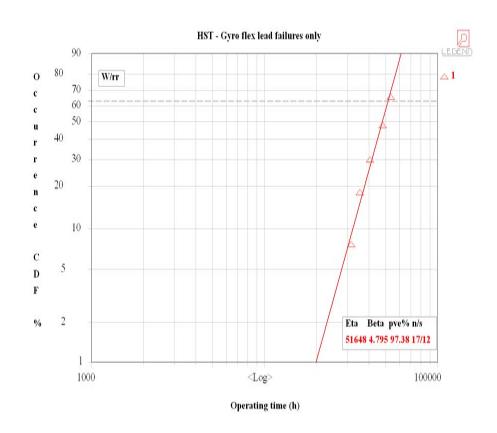
Accounting for non-failed operating times for SF-340 aircraft.

Adding non-failed (suspended) times has increased η substantially (120,000 vs. 31,000 h); β apparently decreased to 1.0 (was 1.3) - but statistically is equivalent.

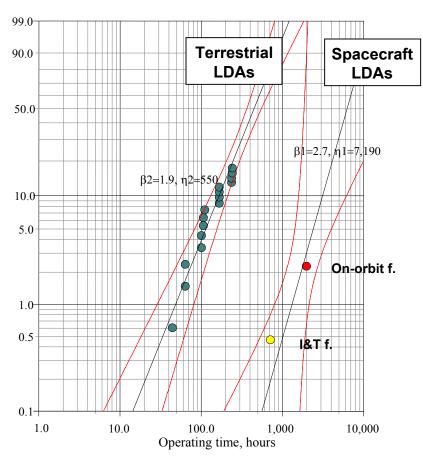
Including suspension times allows predicting <u>fleet</u> in-service wiring failure probabilities.

This is only possible for aircraft which have reliable in-service operating hours data.

- Original HST reliability model used exponential failure distribution (CFR) for gyroscopes.
- HST designed with LRUs for replacing components over its mission lifetime.
- First failures occurred ~ 2y after launch.
- All three RGAs (6 gyros) replaced at SM-1.
- Weibull plot (~1998) identified **wear-out** failure mode; FA had identified **flex lead corrosion** by "inert" suspension fluid.
- Weibull results used to "schedule/select" which gyroscopes to be used and which are standby for mission planning.
- Weibull distribution replaced CFR in Aerospace Corp. system model for future replacements planning.



Hubble Space Telescope Gyroscope Failures



Spacecraft laser diode arrays (LDAs):

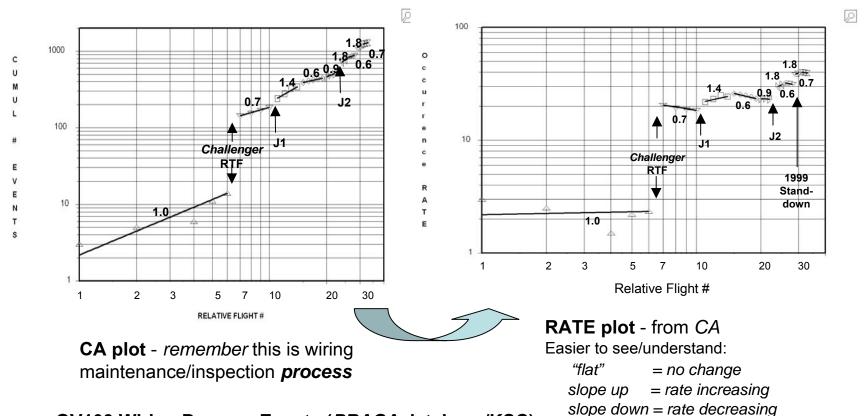
1 f. at I&T - FA indicated "bar blowout"
1 f. ~ 35d after launch - f. cause: Au-In corrosion of wire bonds/thermal fatigue (diode packaging).

Aerospace user of similar LDAs (same mfr) experienced failures; those data showed early wear-out failures. His operating conditions more severe => Weibull plot displaced to left.

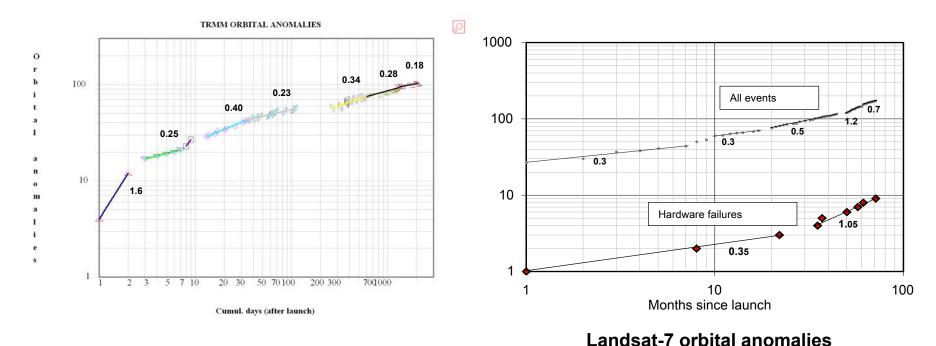
Slopes similar (within statistical confidence).

With **only two failures**, failure predictions for remaining lasers made from this Weibull.

Laser Diode Failures



OV103 Wiring Damage Events (PRACA database/KSC)



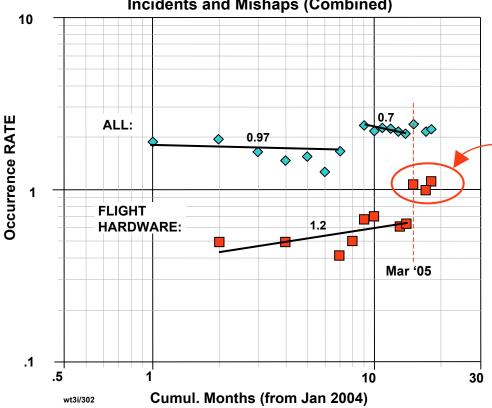
TRMM spacecraft orbital anomaliesBold number adjacent lines are CA slopes

Bold numbers adjacent lines are CA slopes

Hardware failures plot (lower) shows spacecraft still is experiencing random failures; used in life-extension reliability assessment.

SATELLITE ON-ORBIT ANOMALIES

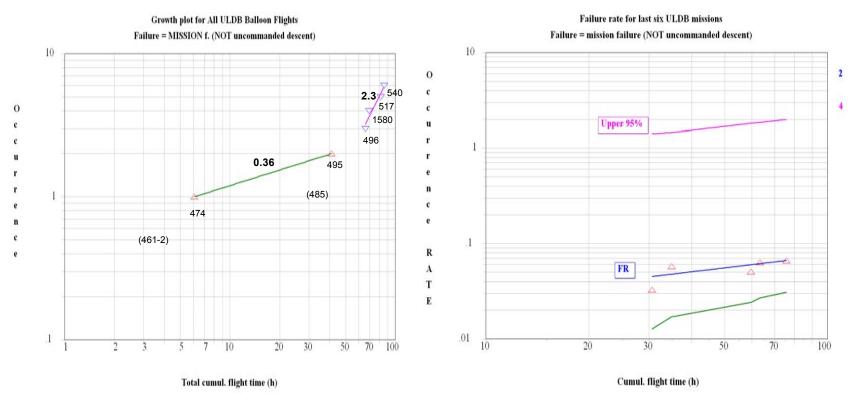




Interpretation: (#'s above fit lines are slopes)

Last three points have poor (statistical) fit; need more time (data from coming months) to resolve slope.

"ALL" after Mar. '05 is influenced by the many Flight Hardware occurrences; last two months data (slope = 2.8) suggests marked increase; monitor future occurrences for trend.



Ultra Long Duration Balloon Development Program -Historical Perspective

ULDB - Flight failure RATE for last 6 flights - after major design change

Conclusions and Lessons Learned:

- 1. Extracting data from databases:
 - Perform keyword searches with care non-relevant "hits" can occur; word matches; misspellings; different descriptions for same occurrence types/modes.
 - Beware of non-relevant and consequential occurrences these can bias extracted statistics.
 - Often, it is advisable to review all (every) event descriptions to verify and classify your data.
 - For determining failure distribution vs. age, need times to failure.
- 2. Use the appropriate statistics according to what you're analysing.
 - Usually, Poisson for event occurrences.
 - Weibull for one failure mode; Crow-AMSAA for multiple modes and other "dirty" data (missing, reliability varies with time).
- 3. Very good, simple-to-use tools for deriving relevant failure/ occurrence distributions and comparing data sets are available.

Data Mining for Text Analysis to Improve Information Access

Mehran Sahami *Google, Inc.*

Mehran Sahami is a Senior Research Scientist at Google, where he conducts research in machine learning technologies applied to a range of information access problems. Prior to joining Google, Mehran was involved in a number of commercial and research machine learning projects, including managing the data mining and advanced technologies groups at Epiphany, and working on research projects at Xerox PARC, SRI International, and Microsoft Research. He received his PhD in Computer Science from Stanford, and still occasionally teaches classes there when he feels like being even more sleep deprived than he already is.

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Clustering & Recurring Anomaly Identification: Recurring Anomaly Detection System (ReADS)

Dawn M. McIntosh
NASA Ames Research Center

Dawn McIntosh has been a Computer Engineer in the Intelligent Systems division at NASA Ames Research Center for five years. For the last two years, she has worked in the Intelligent Data Understanding group, a machine learning and knowledge discovery team, working on text mining and its application to NASA's problem reporting database systems. This work has led to the development of a text mining tool for analysts—the Recurring Anomaly Detection System, ReADS, which clusters problem reports and identifies possible recurring anomalies.

Data Mining Applications in Aeronautics & Space Exploration Workshop



Clustering & Recurring Anomaly Identification: Recurring Anomaly Detection System (ReADS)

Dawn McIntosh

June 21, 2006

NASA Ames Research Center - Intelligent Systems Division

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Credit given to those involved



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 - Eugene Turkov
 - Previous work done by:
 - Brett Zane-Ulman
 - Sakthi Preethi Kumaresan
 - Zuobing Xu
 - Dr. Ram Akella
- NASA ARC, Intelligent Systems Division, Advanced Engineering Network (AEN) Group
 - Dr. David Bell
 - Mohana Gurram
 - Peter Tran
 - Previous work done by:
 - Jenessa Lin
 - Chris Knight

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NASA

Agenda

- What we are trying to accomplish
- What we HAVE accomplished
- Demo ReADS

Problem Introduction



NASA programs have large numbers (and types) of problem reports.

- ISS PRACA: 3000+ records, 1-4 pages each;
- ISS SCR: 28,000+ records, 1-4 pages each;
- Shuttle CARS: 7000+ records, 1-4 pages each;
- ASRS: 27000+ records, 1 paragraph each

These free text reports are written by a number of different people, thus the emphasis and wording vary considerably.

With so much data to sift through, analysts (subject experts) need help identifying any possible safety issues or concerns and to help them confirm that they haven't missed important problems.

- Unsupervised clustering is the initial step to accomplish this;
- We think we can go much farther, specifically, identify possible recurring anomalies.
 - Recurring anomalies may be indicators of larger systemic problems.

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Text Mining - ReADS



Recurring Anomaly Detection System (ReADS):

The Recurring Anomaly Detection System (ReADS) is a tool to analyze text reports, such as aviation reports and maintenance records.

- Text clustering algorithms group large quantities of reports and documents.
 - Reduces human error & fatigue
- Identifies interconnected reports;
 - Automates the discovery of possible recurring anomalies
- Provides a visualization of the clusters and recurring anomalies

We have illustrated our techniques on data from Shuttle and ISS discrepancy reports, as well as ASRS data.

ReADS has been integrated with a secure online search tool: Mishap Anomaly Investigation System,

http://jerusington.aen.nasa.gov:8090/mais-web/

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ReADS Text Mining Algorithms



Unsupervised Clustering:

Spherical k-means → modified von Mises Fisher.

Recurring Anomaly Identification:

- 1. Identify reports which mention other reports as a recurring anomaly
 - a. Using regular expressions to search documents and identify mention of other reports by name.
- 2. Detect recurring anomalies,
 - a. find the similarity between documents to detect recurring anomalies using cosine distance similarity measure,
 - b. then according to the similarity measure, run a hierarchical clustering algorithm to cluster the recurring anomalies.
 - The hierarchical tree is partitioned into clusters by setting a threshold.
 A high threshold implies that the reports could be very different and still be sorted into the same cluster.
 - b. Currently the inconsistency coefficient threshold is set very low, which returns many smaller clusters of very similar reports.

Clusters consisting of only one document are excluded from the recurring anomaly results.

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Evaluation of Clustering Results



- #1 Goal: Don't miss documents identified by the experts as a Recurring Anomaly
- #2 Goal: Get the same results as the experts
- #3 Goal: Find Recurring anomalies missed by the experts.

Criteria:

To meet #1, the ReADS RAs only have to overlap with the experts. The same documents don't have to fall into the same RA clusters. Therefore, if an expert RA cluster contains Docs A, B, & Z, and those documents fall into two ReADS clusters, this is still a success:

Expert Cluster: **A, B, Z**ReADS Cluster: *A, Z*ReADS Cluster: *B, P, M*

To meet #2, an Expert RA cluster should be identical to a ReADS RA cluster.

Expert Cluster: **C, L, R, T**ReADS Cluster: *C, L, R, T*

 To meet #3, ReADS correctly identifies a set of documents which the Experts did not.

Experts Unused Document Cluster: D, E, F, G, H, I, J, K, M, N, O,

P, Q, S, U, V, W, X, Y

ReADS Cluster: F, I, N, D

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Shuttle CARS dataset → Toy Dataset



Shuttle Corrective Action Reporting System (CARS)	Real Dataset (analyzed by experts)	Toy Dataset (selected from Real CARS dataset)	Comments
# of Total Documents	7440	333	344-70=274, selected randomly from 7440-1570 non-RA reports.
# of RA Clusters	366	20	Toy clusters selected to match, as much as possible, a variety of the types of RAs identified by NESC.
# of Total Documents in RA Clusters	1570	70	
Min & Max size of RA Clusters	Min = 2 Max = 48	Min = 2 Max = 10	Toy Dataset RA clusters didn't cover the breadth of the cluster sizes, but the large clusters were rare.

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ReADS stats on Toy Dataset



Shuttle Corrective Action Reporting System (CARS)	Experts Results using Toy Dataset	ReADS Results using Toy Dataset	ReADS Results using Toy Dataset
Similarity Measure Clustering Threshold	NA	0.2 (documents must be very similar to qualify)	0.4 (a less conservative threshold)
# of Total Documents	333	333	333
# of RA Clusters	20	RegEx: 28 SimMeasure: 18	RegEx: 28 SimMeasure: 33
# of Total Documents in RA Clusters	70	RE+SM = 92+56 = 118 (note: There's overlap!)	RE+SM = 92+116 = 208 (note: There's overlap!)
Min & Max size of RA Clusters	Min = 2 Max = 10	Min = 2 Max = 8	Min = 2 Max = 9

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ReADS Cos Similarity Measure (threshold=0.4) Confusion Matrix Stats



Shuttle CARS toy dataset	# of documents in Experts RA clusters	# of documents not in Experts RA clusters	Total =
# of documents in ReADS RA clusters	56	60	116
# of documents not in ReADS RA clusters	14	203	217
Total =	70	263	333

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Toy Dataset Confusion Matrix (threshold=0.4): ReADS cos similarity measure vs. Experts



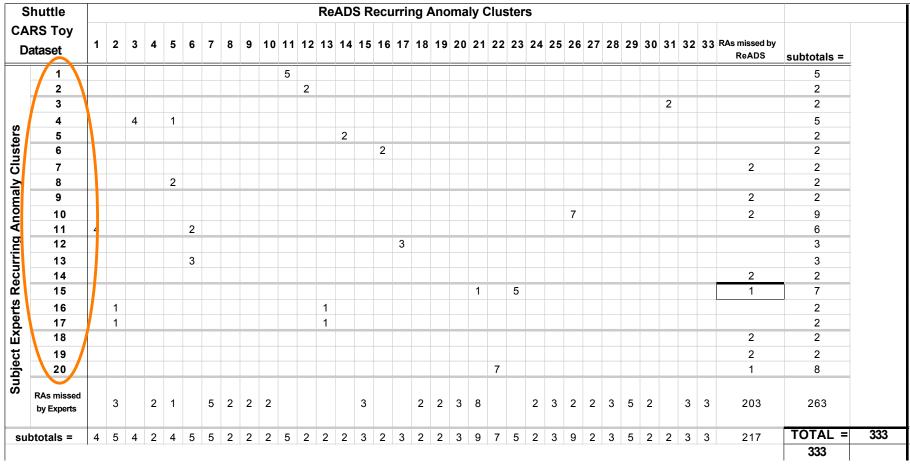
Shuttle									ReADS Recurring Anomaly Clusters																											
CARS Toy Dataset		2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	RAs missed by ReADS	subtotals =	
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Toy Dataset Confusion Matrix: ReADS similarity measure vs. Experts

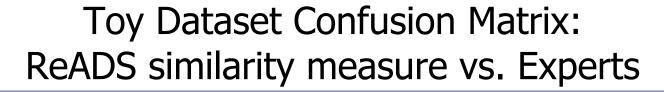




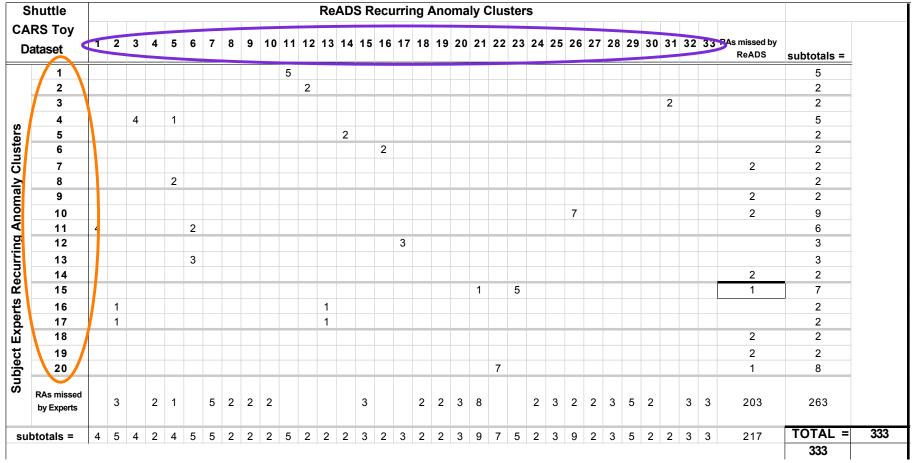
Rows: Recurring Anomaly Clusters identified by Subject Experts

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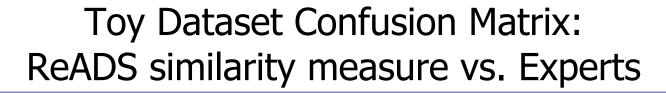


Rows: Recurring Anomaly Clusters identified by Subject Experts

Columns: Recurring Anomaly Clusters identified by ReADS

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Shuttle											R	eAC	S F	Rec	urri	ng .	And	ma	ly (Clus	ster	S														
CARS Toy Dataset	1	2	3	4	5	6	7	8	3 9	1	0 1	1 1:	2 1:	3 14	1 15	5 16	3 17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	RAs missed by ReADS	subtotals =	
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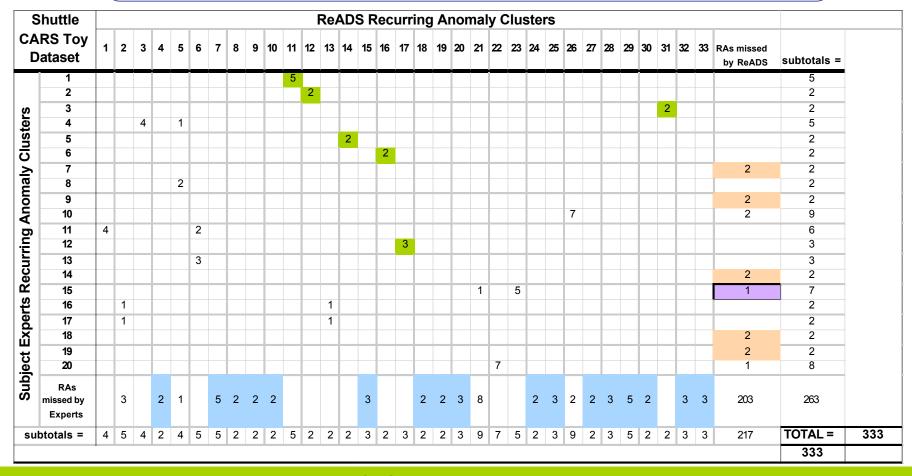
Documents in dataset NOT identified as a RA by Experts Documents in dataset NOT identified as a RA by ReADS

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Toy Dataset Confusion Matrix: ReADS similarity measure vs. Experts





Exact matches between experts and ReADS (Goal #2)

ReADS clusters completely missed by experts (Goal #3)

Expert Clusters missed by ReADS similarity measure algorithm, but caught by the Regular Expression matching (partial failure of Goal #1)

Only document in the toy dataset completely missed by ReADS (failure of Goal #1)

References



Srivastava, A.N., et al., "Enabling the Discovery of Recurring Anomalies in Aerospace Problem Reports using High-Dimensional Clustering Techniques," IEEE Aerospace Conference, Big Sky, MT, March 2006.

Srivastava, A.N. and B. Zane-Ulman, "Discovering Recurring Anomalies in Text Reports Regarding Complex Space Systems," IEEE Aerospace Conference, Big Sky, MT, March 2005.

Banerjee, A. et al., "Generative Model-based Clustering of Directional Data," SIGKDD '03, Washington, D.C., August 2003.

NASA Ames Research Center - Intelligent Systems Division

Summary



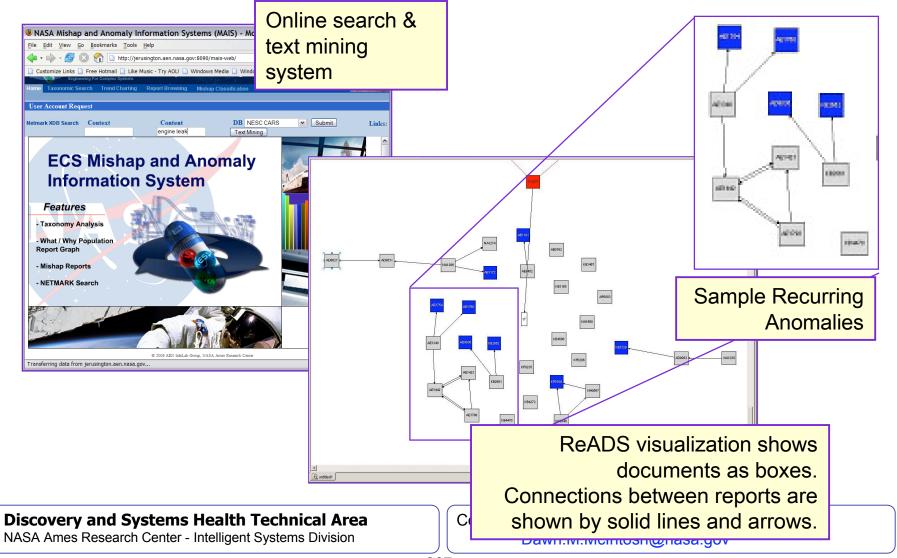
- The ReADS text mining work
- Using the ReADS text mining system on the toy dataset:
 - Only one document was identified by the experts and missed by ReADS.
 - On the other hand, ReADS found many interesting clusters which are possible Recurring Anomalies that the experts may wish to reevaluate.
 - Moreover, by identifying possible recurring anomalies the analysts can quickly focus in on the subset of documents worthy of their time and energy.
 - For the toy dataset of 333 documents, our worst case scenario meant the experts had to read ~208 of those documents (still saves the experts from having to read ~136 documents).
 - Our better scenario has the experts only having to read less than 118 documents – less than 1/3 of the size of the original dataset – a much more manageable set of reports to review!

Discovery and Systems Health Technical Area

NASA Ames Research Center - Intelligent Systems Division

ReADS System & Interactive Visualization



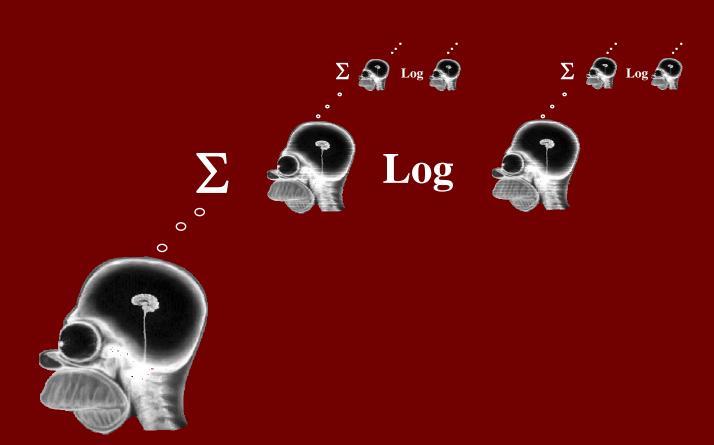


Complexity Measures as Data Mining Tools for Diagnostic MR Imaging

Karl Young *Univ. of California, San Francisco*

Karl Young is a physicist currently working on spatial statistics, image processing, and MR physics at UC San Francisco. After a postdoctoral position at NASA Ames working with Jeff Scargle, he worked in medical physics at UC San Francisco and particle astrophysics on the GLAST project at SLAC before settling in at UC San Francisco.

Complexity Measures as Data Mining Tools for Diagnostic MR Imaging



The Challenge

Large data sets from various magnetic resonance (MR) modalities are available

- structural images (standard MRI T1, T2, ...)
- functional images (fMRI, perfusion, DTI, ...)
- metabolite images (MRSI)
- But analysis is complex, error prone, and hard to interpret

The Proposed Solution

 Combine images from multiple modalities (i.e. into a "high dimensional feature space")

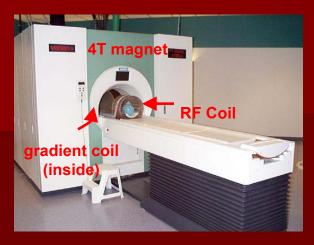
 Analyze combined images using information theory based techniques (aka complexity)

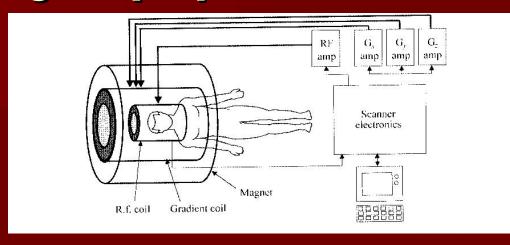
Outline of Talk

 Part I – Description of MR Imaging Data (even though we're data mining we might want to know something about our data...
)

 Part II – Application of Complexity Measures To analysis of Multimodal MR Image Analysis

Necessary Equipment





Magnet



Gradient Coil



RF Coil

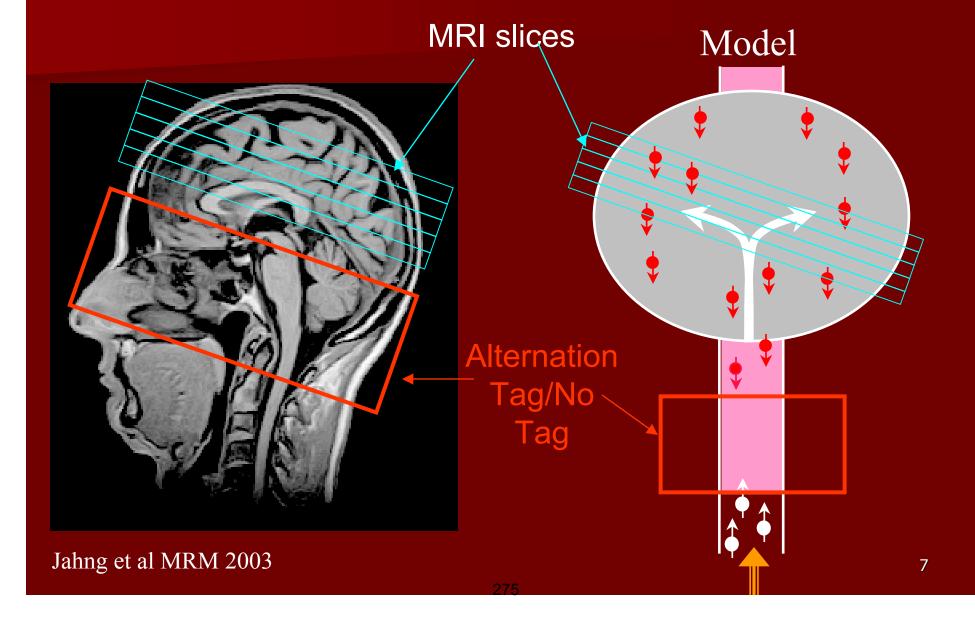


Source: Joe Gati, photos

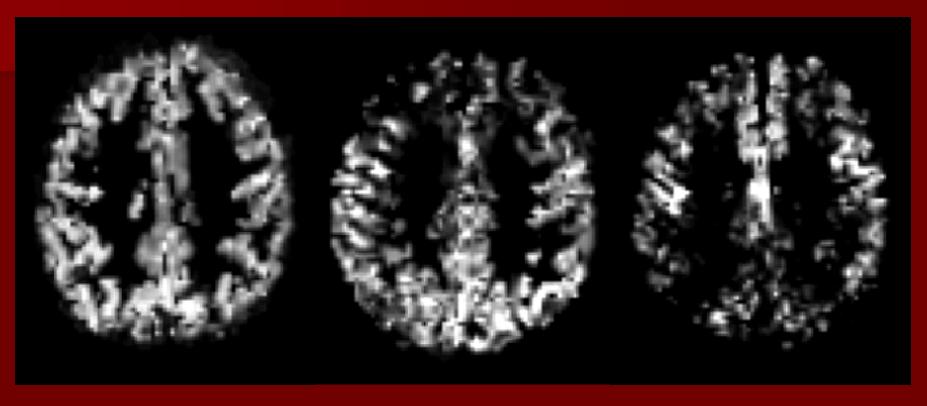
What Can Be Done With A Big Magnet - MR Imaging Modalities

- Standard Structural MRI measures contrasts based on fact that magnetization decays at different rates for different materials (e.g. tissue types)
- Perfusion Imaging maps cerebral blood flow
- Diffusion Tensor Imaging measures direction and rate of diffusing protons
- Spectroscopic Imaging measures concentration of brain metabolites

Pulsed Arterial Spin Labeling (ASL) Perfusion MRI



Representative ASL-MRI Data



Cognitive Normal

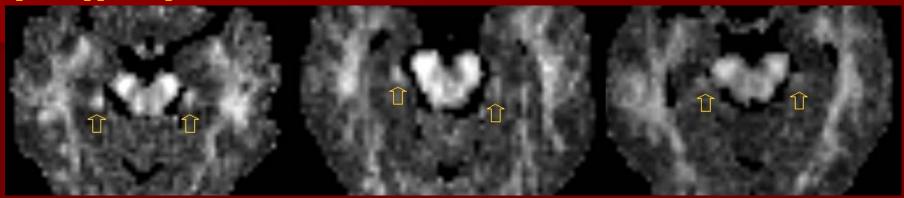
Frontal Temporal Dementia Alzheimer's Disease

Diffusion Tensor Imaging (DTI)

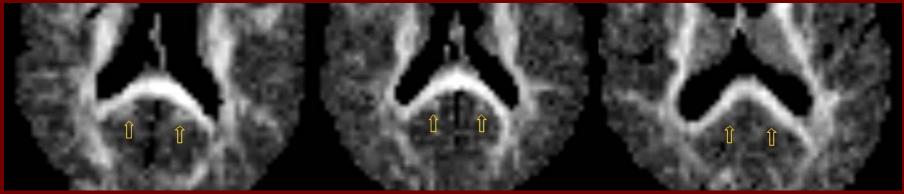
- Diffusion in the presence of a non-uniform magnetic field (e.g. applied gradient) causes signal loss due to dephasing.
 - i.e. spin diffuses to new position (with different field strength)
 - -> changes precession frequency
 - -> is, on average, out of phase with neighboring spins

Signal Variation in Fractional Anisotropy (FA) Images

parahippocampus



posterior cingulate



Cognitive Normal

Mild Cognitive Impairment

Alzheimer's Disease

In Vivo MR Spectroscopy

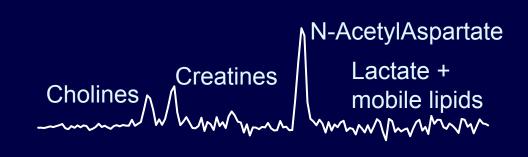
- Background
 - Local magnetic field seen by nucleus varies slightly based on environment (e.g. what position it's in, in molecule)
 - Enables non-invasive analysis of tissue chemistry
 - Uses same technology as MRI
 - Particularly benefits from higher field strength

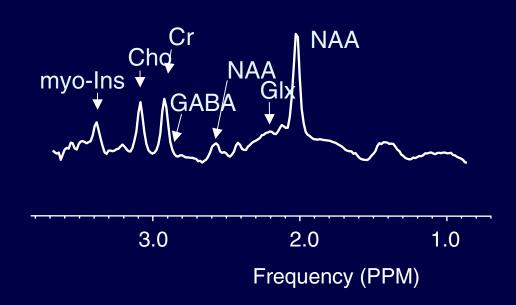
The In Vivo ¹H NMR Brain Spectrum

TE = 136 ms

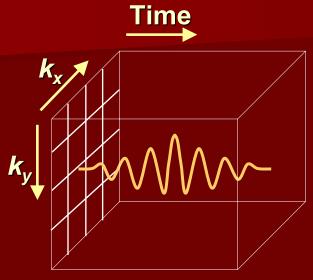
TE = 30 ms

1.5 Tesla



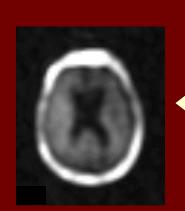


Basic Phase-Encoded MRSI



Each k_x , k_y data obtained as a separate measurement.

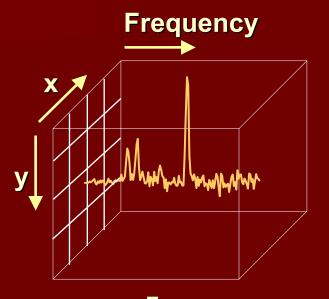
Metabolite images formed by spectral integration at each voxel

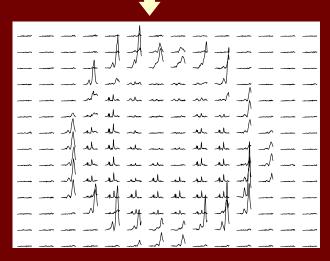


3D Fourier transform

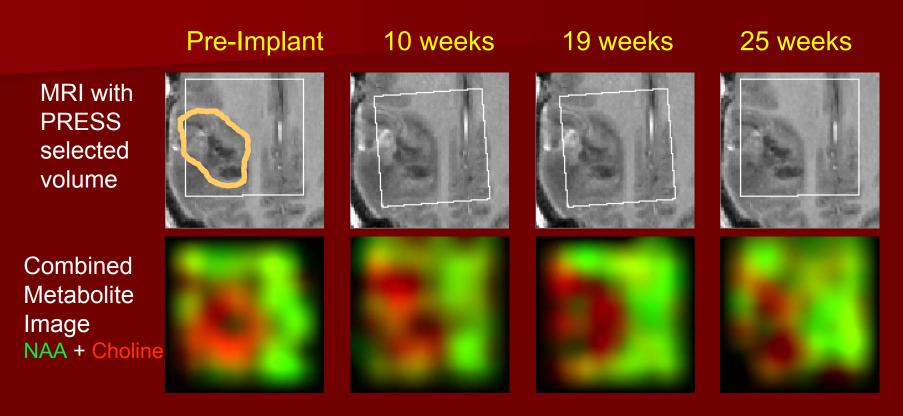


(+ filtering, phase correction, water subtraction)





Evaluation of Treatment Response



Uses serial ¹H MRSI studies with MRI-based spatial coregistration to align metabolite images to monitor changes in the metabolite distributions in response to therapy.

L.L. Wald et al. Serial proton magnetic resonance spectroscopy imaging of glioblastoma multiforme after brachytherapy. *J. Neurosurg.* 87,525, 1997

Can We Do More?

MR Modalities Useful for Specific Targeted Diagnosis

 But Only A Small Fraction of Information in Images Has Been Utilized

■ Can We "Mine" More Information? How?

A Proposal

 Use Complexity Measures To Classify and Characterize Brain State (e.g. Stage of Neurodegenerative Disease) from Multimodal MR images

Science

What Are Complexity Measures?

Complexity

Many <u>strongly interacting</u> components introduce an inherent element of uncertainty into the observation of a complex (nonlinear) system like the brain

Good Reference:

W.W. Burggren, M. G. Monticino. Assessing physiological complexity. *J Exp Biol*. 208(17),3221-32 (2005).

Early "Physical" Complexity Measures

Arose in context of using ideas from computer science and information theory to solve classical inverse problem (inductive inference) for nonlinear, chaotic systems:

DATA ----- MODEL

Complexity/Information Measures Used

Metric Entropy – measures number, and uniformity of distribution over observed patterns

Symbolic Dynamics of Noisy Chaos

J. P. Crutchfield and N. H. Packard Physica **7D** (1983) 201-223.

Statistical Complexity — measures correlations over observed patterns

Inferring Statistical Complexity

J. P. Crutchfield and K. Young Physical Review Letters **63** (1989) 105-108.

Excess Entropy – measures convergence rate of Metric Entropy

<u>Structural Information in Two-Dimensional Patterns: Entropy Convergence and Excess Entropy</u>

D. P. Feldman and J. P. Crutchfield Santa Fe Institute Working Paper 02-12-065

Analysis of MR data via Complexity/Information Measures

Fundamental Intuition:





Basic question: How does P(q2|q1) vary as function of q1,q2, and shape?

Joint Histogram P(q2,q1)

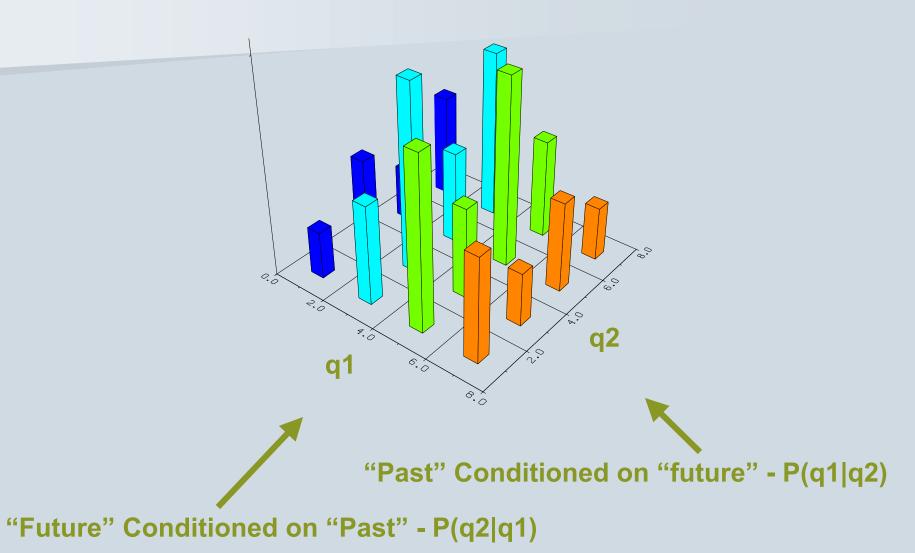


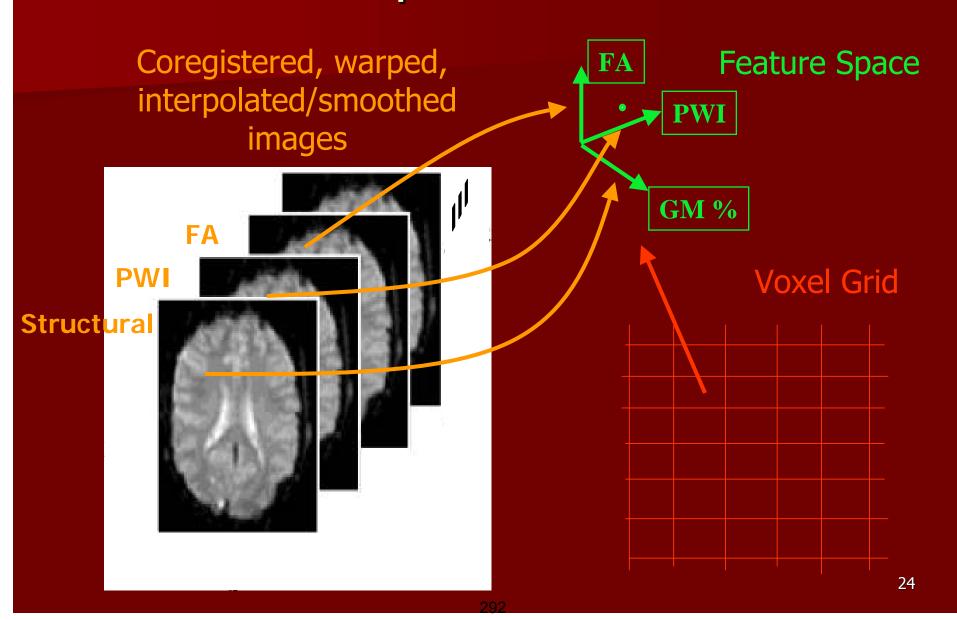
Image Analysis Proceeds in 4 Stages

- I. Choice of appropriate Feature Space (e.g. coregistered structural MRI, DTI, MRSI data)
- II. Segmentation (Clustering) of Feature Space
- III. Generation of Complexity Measures as Summary Variables
- IV. Classification Based on Summary Variables (e.g. supervised – LDA, SVM, Bayes Nets, Random Forests,...)

Stage I - Choice of Appropriate Feature Space

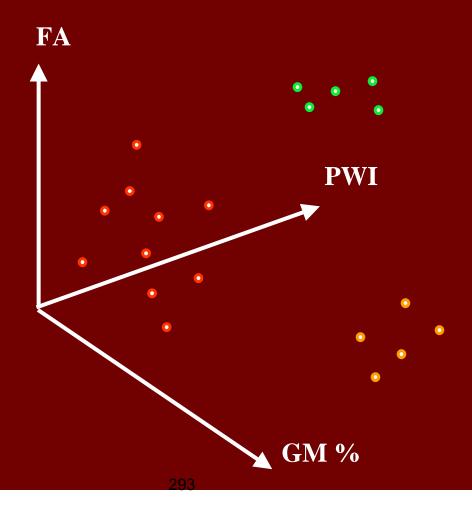
- Utilize prior information
 - E.g. for studies of neurodegenerative disease might choose structural (MRI)+ functional (Perfusion) + metabolic (NAA, glutamate,... levels) information
- Feature space visualization useful for choosing appropriate variables (e.g. scatter plot matrices) canonical case for use of Exploratory Data Analysis

Feature Space Construction

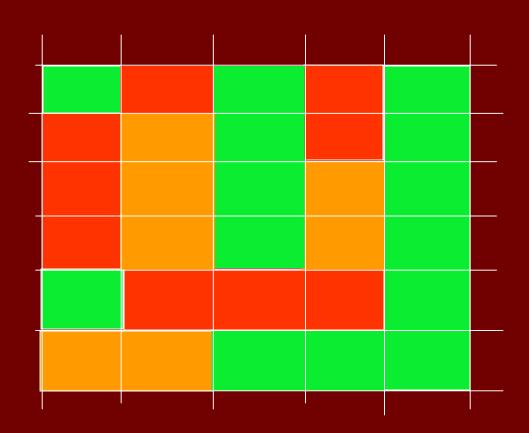


Stage II - Segment Feature Space (I.E. Find Clusters)

For whole image – i.e. features from all voxels



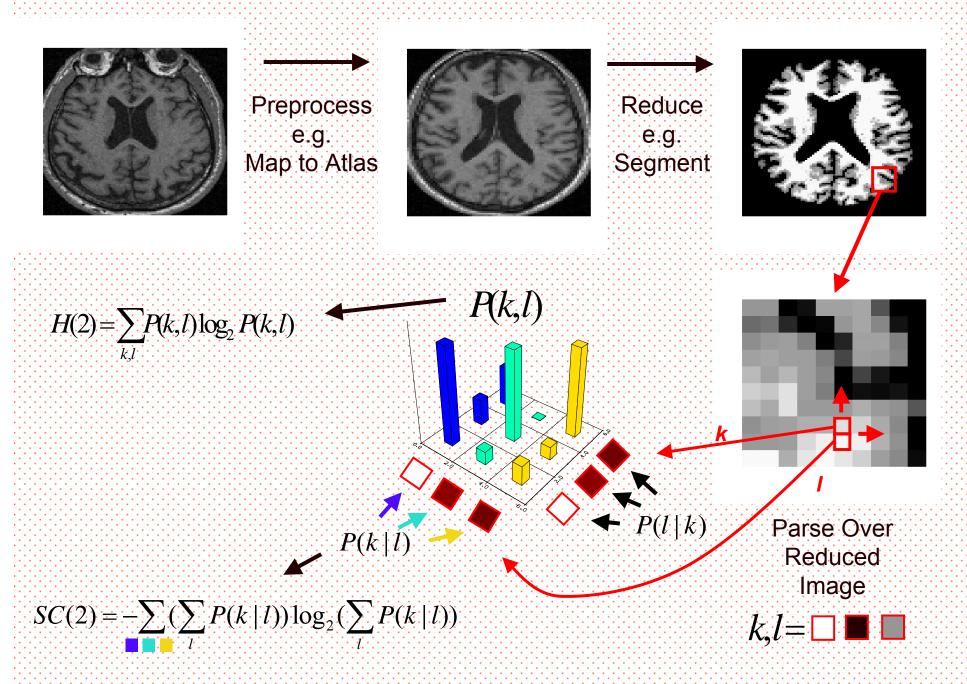
Map Discrete Segment Features Back To Voxel Grid



Stage III - Use of Information Measures for Generation of Summary Variables

Generate joint distribution by parsing labeled image

Calculate information measures from joint distribution



Simulation – Cortical Thinning In Right Superior Temporal Gyrus (RSTG)

■ Data - 50 subjects from ICBM Data Base of "normal" subjects (to try and account for normal population variation) — 25 with artificial thinning in RSTG (by an average of 0.5 mm), and 25 "controls"

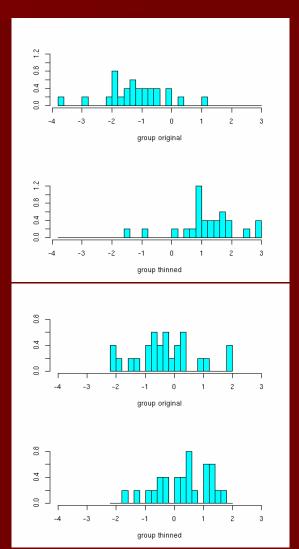
J. P. Lerch, A. C. Evans. Cortical thickness analysis examined through power analysis and a population simulation. *Neuroimage*. 24(1):163-73 (2005).

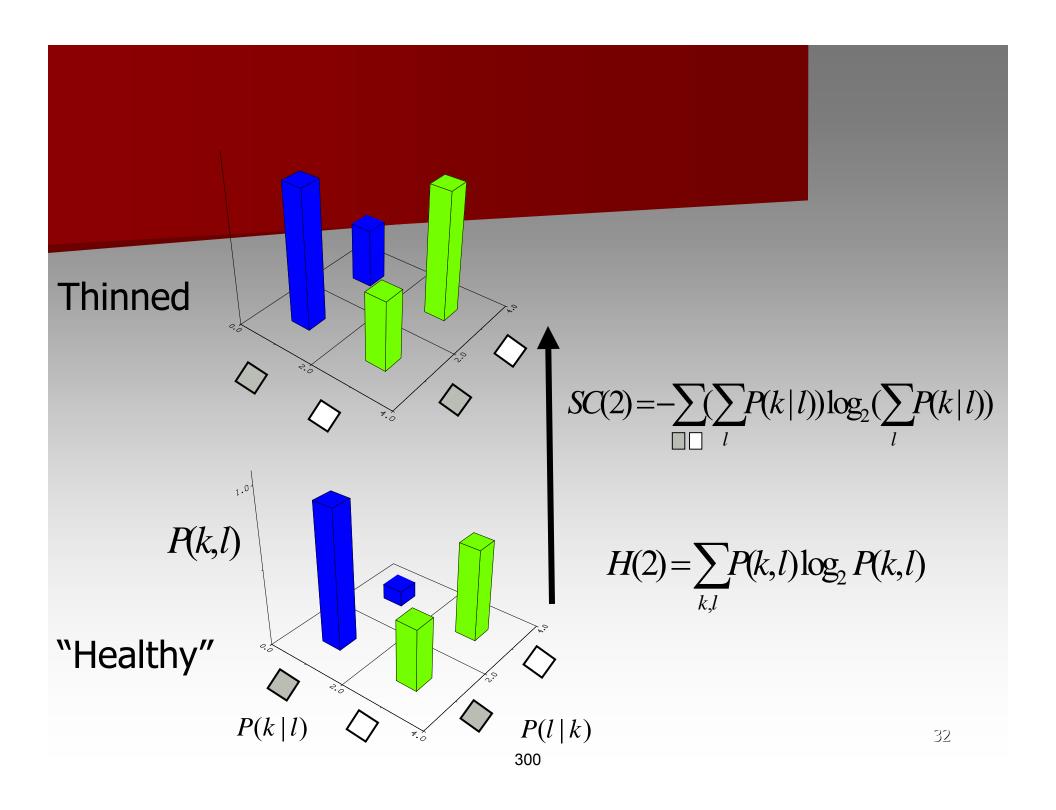
Simulation – Cortical Thinning In Right Superior Temporal Gyrus (RSTG)

	MANOVA p	LDA p	SENS.	SPEC.
WB	0.19	2.9e-02	0.59	0.52
TL	2.3e-03	2.0e-04	0.73	0.63
STG	6.6e-06	1.7e-07	0.80	0.76
LSTG	0.20	3.0e-02	0.60	0.55
RSTG	4.1e-09	5.7e-11	0.91	0.85

Simulation – Cortical Thinning In Right Superior Temporal Gyrus (RSTG)

EE **RSTG** Н SC 0.24 0.26 0.28 0.30 EE **LSTG**





Preliminary Analysis of CN, AD, and FTD Subjects

 Given results of previous simulation, reasonable next step - comparison with current set of 66 subjects (25 CN, 21 AD, and 20 FTD) currently under study for cortical thinning

Preliminary Analysis of CN, AD, and FTD Subjects

- Analysis: Used standard software (SPM) to generate segmented images (modified mixture model cluster analysis) and map to MNI atlas
- Chose 13 regions (from the literature) expected to be affected in AD, FTD, or both

Very Preliminary Results

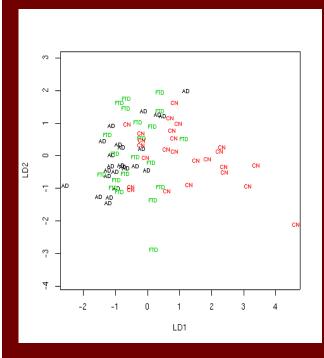
	MANOVA p	LDA prediction accuracy
Whole Brain	1.4e-06	0.64
Hippocampus, Subiculum, Precuneus	2.4e-08	0.80
13 Regions	7.1e-04	0.96

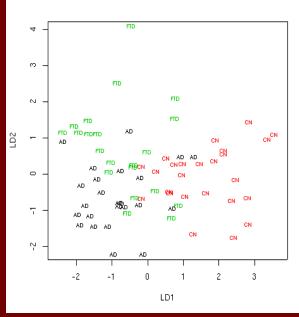
Preliminary Results

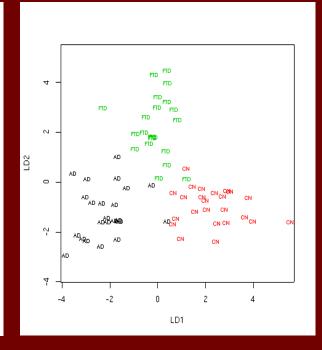
Whole Brain

Hipp., Sub., Pre.

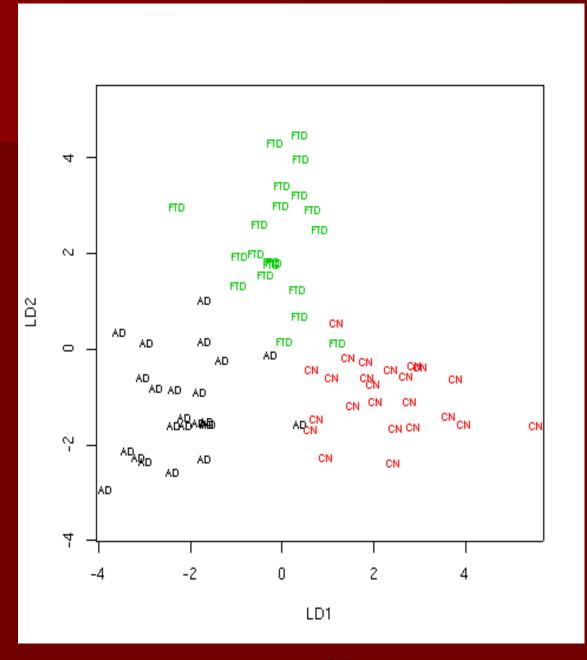
13 Regions







13 Regions



Conclusion

Complexity/Information Measures
 Generate Sensitive Diagnostic Information
 From Multimodal MR Images

Collaborators – Yue Chen, John Kornak,
 Gerald Matson, and Norbert Schuff